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Hazardous Weather and Human Response in the Southeastern United States

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To the Graduate Council:

I am submitting herewith a dissertation written by Daniel Burow entitled "Hazardous Weather and Human Response in the Southeastern United States." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Geography.

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Hazardous Weather and Human Response in the Southeastern United States

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Abstract

Effectively mitigating the human costs of future hazardous weather events requires examining meteorological threats, their long-term patterns, and human response to these events. The southeastern United States is a region that has both a high climatological risk and a high societal vulnerability to many different meteorological hazards. In this dissertation, I study hazardous weather and human response in the Southeast through three different lenses: identifying uniquely simultaneous hazards posed by tropical cyclones, assessing precipitation and synoptic weather patterns on hazardous weather days, and examining patterns in intended response to tornado watches. I find that simultaneous and collocated tornado and flash flood warnings are common in strong tropical cyclones, particularly those that move slowly after landfall. Additionally, hazardous weather days are common on days dominated by Moist Moderate and Moist Tropical airmasses and airmass transition days. Finally, factors including age, income, self-efficacy beliefs, and knowledge of and experience with tornadoes affect one's intended response to a tornado watch. These studies produce new contributions to the state of knowledge on both the natural and social elements of hazards studies.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Introduction

Meteorological events such as tornadoes, floods, and tropical cyclones become disasters when they affect human society by endangering human lives or destroying portions of the built environment. As global populations increase and the built environment expands, more people and capital will be exposed to hazardous weather events, and potential for disaster will increase. Such increases in natural disaster loss have been observed or projected for tornadoes (Ashley *et al.* 2013, Simmons *et al.* 2013, Ashley and Strader 2015), tropical cyclones (Pielke *et al.* 2008, Peduzzi *et al.* 2012, Freeman and Ashley 2017), and floods (Hirabayashi *et al.* 2013, Ferguson and Ashley 2017). Mitigating future loss necessitates progress in understanding both the natural and social elements of disasters.

Geography plays a key role in determining the number of casualties and amount of societal disruption and economic loss produced by hazardous meteorological phenomena. Events causing the highest loss and disruption often occur in well populated areas, illustrating the connection between human disaster potential and the built environment. Recent examples of this pattern include the April 2011 Tuscaloosa-Birmingham and the 2011 Joplin, Missouri, tornadoes that killed 64 and 162 people, respectively (Paul and Stimers 2012, Roueche and Prevatt 2013). Long-term studies have established that population and expanse of the built environment within the footprint of the tornado damage path is a key factor in the number of casualties and amount of damage caused by that tornado (Ashley *et al.* 2013, Strader *et al.* 2015, Fricker *et al.* 2017, Elsner *et al.* 2018). A similar pattern is true for tropical cyclones (TCs). TCs producing high casualties include Hurricane Katrina (2005) and Hurricane Harvey (2017), whose landfall locations near the New Orleans and Houston metropolitan areas contributed to the high loss of life (Brunkard *et al.* 2008, Jonkman *et al.* 2018). Effects of hazardous winter weather are also location dependent. While direct attribution of fatalities to winter weather is difficult, several proposed metrics of winter storm severity take into account the population of the regions affected (Zielinski 2002, Kocin and Uccellini 2004, Cerruti and Decker 2011).

Several factors determine how vulnerable a given location or society is to disasters. Among them are its climatological exposure to extreme events, as defined by the frequency and magnitude of these extreme events at that location; its sensitivity to damage from these events; and its capacity to adapt to and rebuild from damage caused by these events (Morss *et al.* 2011). Of these factors, climatological exposure is effectively impossible to alleviate, although it can be quantified and monitored, as this would entail preventing extreme weather events from occurring in the first place. However, hazard sensitivity and adaptive capacity can be improved through sustainable planning and mitigation strategies (Morss *et al.* 2011). Quantifying the likelihood of, anticipating changes in, and evaluating public response to hazardous weather are important strategies to achieving this goal. As Earth's climate and human populations are both constantly in flux, monitoring trends in both variables and the interaction between them is necessary to safeguard future societies from the threat of disasters. Attributing losses from catastrophic weather events to changes in Earth's climate is a complex task (Huggel *et al.* 2013), and population expansion may play as big of a role in these increased losses as climate change (Mohleji and Pielke 2014).

1.2 The Dissertation

The theme of this dissertation is to examine hazardous weather in the Southeast U.S. through three different lenses:

1. Identifying uniquely simultaneous hazards—tornadoes and flash floods during TCs—that can cause confusion amongst members of the public.
2. Assessing patterns in precipitation and synoptic weather types of hazardous weather days at major NWS observation stations.
3. Examine patterns in intended response to hazard alerts—tornado watches—that have received little research attention.

The dissertation is comprised of five chapters. Chapter 1 provides a background to hazards research and the climatology of the Southeast. Chapters 2, 3, and 4 consist of individual studies aimed at one of the three lenses above, each with its own unique study area and specific research goals. Versions of these studies are either in revision for publication in peer-reviewed research journals, or soon will be in review.

Chapter 2 examines hazardous weather through the first lens listed above. I use archives of tornado and flash flood warnings that occurred in TC environments to identify where they intersected both spatially and temporally, and examined patterns in location, size, and duration of these overlapping warnings. Finally, I determine TC characteristics that are associated with producing simultaneous tornado and flash flood warnings.

Chapter 3 explores hazardous weather events in the Southeast through the second lens. I identify hazardous weather days at 40 locations using NWS warnings for a number of meteorological hazards. I quantify the amount of precipitation that occurs on these days and assess the dominant synoptic weather types on these days using a classification system that is well-established in previous studies. I then identify modes of precipitation on hazardous weather days and examine seasonal trends in these modes.

Chapter 4 examines public response to hazardous weather; the third lens of this dissertation. I use survey data of Tennessee residents to elucidate common patterns in intended responses to tornado watches that may affect one's preparedness to seek shelter should a tornado strike. I analyze the ways in which psychological and sociodemographic factors are associated with intended watch response and compare these patterns to those identified by prior research on tornado hazard response.

Finally, Chapter 5 summarizes the conclusions from the research in Chapters 2 through 4. I then draw connections to current research efforts relevant to these topics and discuss possible directions and goals for future research.

1.3 Study Area

The three research chapters in this dissertation each have different study areas depending on the goals of each study, but the general focus of all three is on the southeastern U.S. (Figure 1.1). This is a region of the country with an elevated long-term rate of mortality due to natural hazards, particularly in the lower Mississippi Valley, northern Alabama, and Florida Panhandle (Borden and Cutter 2008). There are a number of social and demographic reasons for this high vulnerability, including language barriers, housing stock, poverty, and climatological risk to extreme events (Cutter *et al.* 2003, Ashley 2007, Borden *et al.* 2007, Sutter and Simmons 2010).

The southeastern U.S. is vulnerable to many types of hazardous meteorological events, including tornadoes, flooding, tropical cyclones, hazardous winter weather, and damaging wind and hail. Tornadoes are common in the region (Coleman and Dixon 2014, Fuhrmann *et al.* 2014) and tornado-favorable environments have become more frequent in the Southeast, especially relative to the Great Plains (Gensini and Brooks 2018). Nocturnal tornadoes, which are more

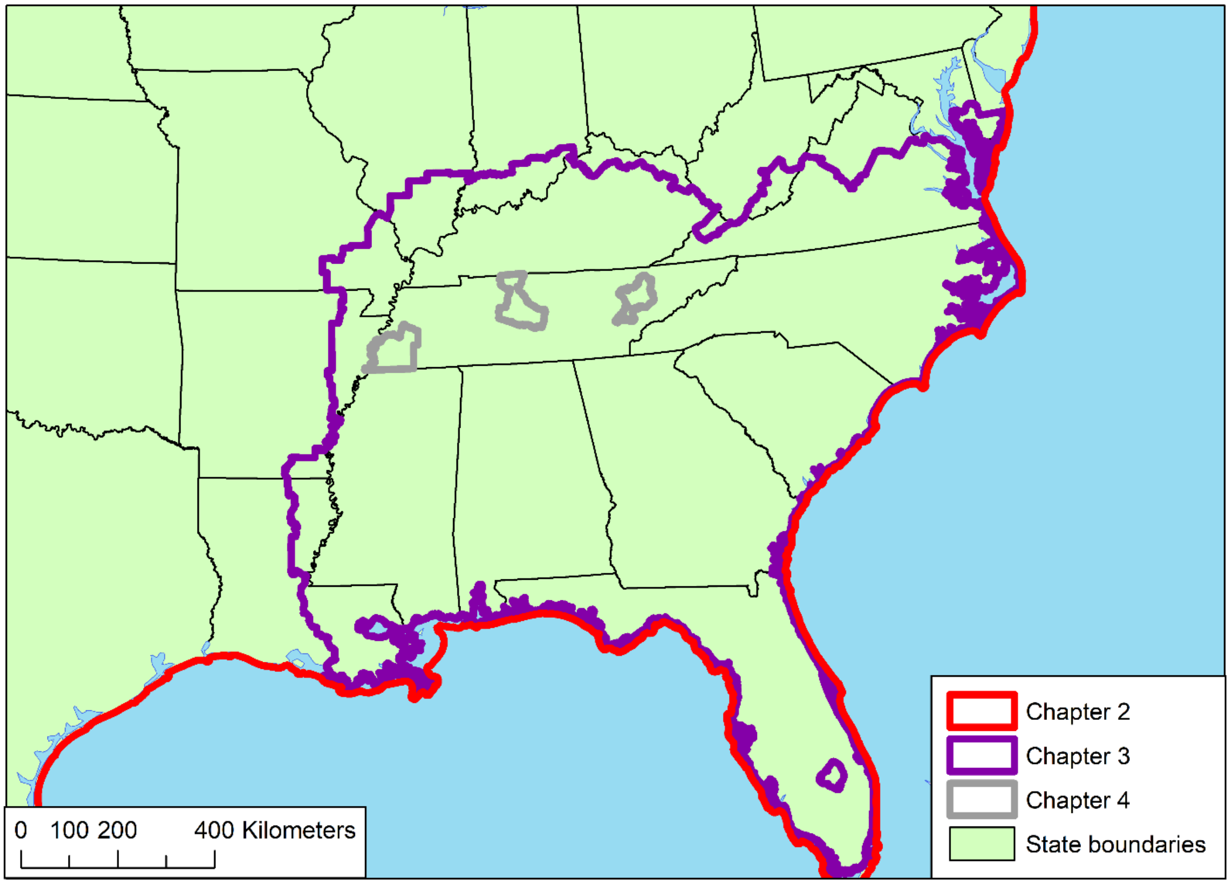

Figure 1.1. Study area extents for the three research chapters in this dissertation.

likely to cause fatalities, are more common in the Southeast than in any other region of the country (Ashley *et al.* 2008a). Mobile homes offer insufficient protection to tornadoes but comprise a substantial proportion of the housing stock in the Southeast (Sutter and Simmons 2010, Strader and Ashley 2018). Members of the public commonly misunderstand their own location's climatological risk to tornadoes and perceived protections from topographic features (Ellis, Mason, *et al.* 2018, Ellis *et al.* 2019), and expansion of the built environment across the region is expected to increase the number of lives and amount of property exposed to tornadoes (Ashley and Strader 2015). As a result, the fatality rate for tornadoes in the Southeast is higher than for other regions of the country (Ashley 2007, Fricker *et al.* 2017, Elsner *et al.* 2018).

Tropical cyclones (TCs) are another meteorological threat to the region. Tropical storm or hurricane-caliber events affect coastal regions of the Southeast with return periods of less than a decade in many locations (Keim *et al.* 2007). Each TC presents its own unique combination of wind-, flood-, and surge-related hazards (Senkbeil and Sheridan 2006, Senkbeil *et al.* 2011) and they can even produce deadly tornadoes (Moore and Dixon 2012). Like tornadoes, population expansion in coastal, TC-prone regions has collocated people and property with hazard risk, and this pattern is likely to continue in the future (Wilson and Fischetti 2010, Freeman and Ashley 2017).

Flood events are common during all seasons in the Southeast (Dougherty and Rasmussen 2019), induced by frontal boundaries, TCs, and other forcings (Ashley and Ashley 2008a, Barlow 2011). Floods killed nearly 100 people per year in the U.S. from 1959 to 2005, many of which occurred in the Southeast (Ashley and Ashley 2008b). Severe, nontornadic windstorms also cause fatalities in the region (Black and Ashley 2010), and while hail and winter storms rarely kill people directly, they do occur in the Southeast and cause economic loss (Changnon and Karl 2003, Changnon 2007, Cintineo *et al.* 2012).

1.4 Relevance to current research priorities

This dissertation uses elements of *convergence research*, or research that uses cross- and multidisciplinary approaches to address complex, real-world problems. While multidisciplinary research efforts are not new, there has been a recent emphasis on convergence approaches within organizations such as the National Science Foundation (NSF). The NSF provides two key characteristics of convergence (NSF 2019):

1. *Research driven by a specific and compelling problem*. Convergence research is generally inspired by the need to address a specific challenge or opportunity, whether it arises from deep scientific questions or pressing societal needs (NSF 2019).
2. *Deep integration across disciplines*. As experts from different disciplines pursue common research challenges, their knowledge, theories, methods, data, research communities and languages become increasingly intermingled or integrated. New frameworks, paradigms or even disciplines can from sustained interactions across multiple communities (NSF 2019).

The first characteristic is applicable to meteorological and climatological hazards because these events produce pressing societal needs by endangering life and property. Tornadoes (Simmons and Sutter 2005, Simmons *et al.* 2013), tropical cyclones (Pielke *et al.* 2008, Czajkowski *et al.* 2011, Bakkensen and Mendelsohn 2016), and floods (Ashley and Ashley 2008b, Doocy *et al.* 2013) inflict casualties and economic loss every year in the U.S. and across the globe. Each of these phenomena and their elements that threaten human society in the southeastern U.S. are examined in this dissertation.

The second characteristic of convergence research is applicable to this dissertation through its multidisciplinary nature. Multi- and cross-disciplinary methods are powerful approaches to complex problems involving social and environmental elements, particularly research on hazards and disasters (Morss *et al.* 2018, Behrendt *et al.* 2019). These "convergent-like" efforts have played a key role in reducing potential loss from meteorological disasters (Peek *et al.* 2020). With this dissertation, I aim to produce novel and significant contributions to the field of Geography by drawing techniques from adjacent disciplines.

The purpose of this dissertation matches well with the goals of public research entities including the National Oceanic and Atmospheric Administration (NOAA) and the National Weather Service (NWS), which serve the people of Tennessee and the southeastern U.S. NOAA's mission, titled "Science, Service, and Stewardship", includes efforts "[t]o understand and predict changes in climate, weather, oceans, and coasts" as well as "[t]o share that knowledge and information with others" (NOAA 2021c). By exploring climatological patterns of hazardous weather in the Southeast in Chapter 3, my work here aids in understanding these patterns in a way that can be used in the future to determine and anticipate changes. Furthermore, by examining public response to hazardous weather in Chapter 4, findings from this dissertation shed light on more effective ways to communicate severe weather information and alerts to members of the public who may be endangered.

Like NOAA, the mission of the NWS is to "[p]rovide weather, water, and climate data, forecasts, and warnings for the protection of life and property and enhancement of the national economy" (NWS 2021a). Findings from Chapters 2 and 3 of this dissertation add to the weather and climate data available to be consulted and disseminated for NWS procedures. Additionally, in Chapter 2, I examine when, where, and how often NWS warnings may create confusion that inhibits the utility of these warnings to protect life and property.

One of the strategic plans of the NWS is to create a "Weather-Ready Nation" (WRN), in which "communities across the country are ready, responsive, and resilient to weather, water, and climate threats" (NWS 2021b). This plan was launched in 2011, shortly before the April 2011 tornado outbreak that killed over 300 people, many in the Southeast. Connecting NWS analysis and alerts to societal impacts has been identified as a vital step in bridging the gap between forecasters and members of the public (Uccellini and Hoeve 2019). Ensuring that messages given by NWS alerts are properly received and understood by the public has been a core element to building a WRN since the beginning of this effort and is investigated in Chapters 2 and 4 of this dissertation (Moore *et al.* 2012).

Chapter 2

Simultaneous and collocated tornado and flash flood warnings associated with tropical cyclones in the contiguous United States

A version of this study was originally published by Daniel Burow, Kelsey Ellis, and Liem Tran in the *International Journal of Climatology*, and the following chapter is adapted from that manuscript. My use of "we" in this chapter includes these coauthors. I served as first author, and my contributions included study design, data collection, analysis, and manuscript writing. Kelsey Ellis' and Liem Tran's contributions included study design and manuscript editing.

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2.1 Abstract

Simultaneous and collocated tornado and flash flood (TORFF) warnings are a dangerous hazard because the recommended protective action for the two threats are opposite, leaving residents unsure if they should shelter below or seek higher ground. Tropical cyclones (TCs) cause both tornadoes and flash flooding and are thus favorable environments for TORFF warnings. In this study, we provide a unique examination of TORFF warnings in 32 TCs that made landfall in the contiguous United States between 2008 and 2018. We identify TC TORFF warning characteristics including duration, area, distance from coastline, geographic location, and location relative to TC center, and we compare these results to established findings on TC tornadoes. We found that TORFF warnings were geographically most common in the states of Texas, Louisiana, and Mississippi, and within 200 km of the coastline. TORFF warnings occurred almost exclusively east of TC center. When compared to TC tornadoes, TORFF warnings were relatively more frequent nearer to the coastline and in the right-back quadrant of the TC. Over half (59%) of the 32 TCs we studied produced at least one TORFF warning. Using logistic regression, we determined that TC intensity effectively determines how likely a TC is to

produce at least one TORFF warning, while TC translational velocity determines how likely a TC is to produce many TORFF warnings. Thus, intense TCs were likely to produce at least a few TORFF warnings, while intense and slow-moving TCs were likely to produce many TORFF warnings. These findings establish a knowledge base on the climatological characteristics of this unique and dangerous hazard.

2.2 Background

Tropical cyclones (TCs) pose a major threat to low- and mid-latitude regions across the globe. The southeastern U.S. is one such region that is frequently affected by destructive TCs (Keim *et al.* 2007, Malmstadt *et al.* 2010, Ellis *et al.* 2015). TCs present a number of hazards, including storm surge; torrential rainfall and flooding; damaging winds; and tornadoes, causing fatalities and economic loss (Pielke *et al.* 2008, Czajkowski *et al.* 2011, 2017, Rappaport 2013). Our focus in this study is on two specific TC hazards: tornadoes and flash flooding.

Thousands of tornadoes associated with TCs have been observed in the U.S. (Schultz and Cecil 2009, Moore and Dixon 2011, Edwards *et al.* 2012). The number of tornadoes produced by a given TC can vary drastically, but stronger TCs tend to produce more tornadoes because low-level wind speeds are greater, enhancing vertical shear values. TCs making landfall along the Gulf of Mexico are also more prolific tornado producers because the tornado-favorable right-front quadrant of the TC is over land (Verbout *et al.* 2007). Most TC tornadoes occur near the coastline shortly after landfall (Schultz and Cecil 2009), but tornadoes occurring farther inland tend to be stronger and cause more damage as the TC encounters greater vertical wind shear associated with the jet stream (Verbout *et al.* 2007, Moore and Dixon 2015, Moore *et al.* 2017).

Meteorologists at the National Weather Service (NWS) issue tornado warnings when a tornado has been spotted or is imminent (Brotzge and Donner 2013). The recommended protective action during a tornado warning is to shelter in the lowest available level of a building (NOAA 2020a). Fatality rates tend to be higher for those who ignore these warnings and do not take shelter (Hammer and Schmidlin 2002, Paul and Stimers 2012).

Flooding is another common TC-related hazard. Flash flooding can occur in regions of intense TC precipitation, even in locations far from the coastline (Villarini *et al.* 2011, Villarini, Goska, *et al.* 2014, Aryal *et al.* 2018). Several recent studies have suggested that urban areas with impervious land covers are particularly vulnerable to flash flooding (Zhou *et al.* 2017, Hung *et al.* 2018, Zhang *et al.* 2018). This is especially concerning because flooding already accounts for over a quarter of TC-related fatalities (Rappaport 2013), often in areas far from the location of TC landfall (Czajkowski *et al.* 2011, 2017), and future expansion of the built environment in TC-prone regions of the U.S. is anticipated (Freeman and Ashley 2017).

Flood warnings, like tornado warnings, indicate that flash flooding conditions are ongoing or imminent. NWS meteorologists forecast flash flooding events using rainfall and runoff estimations, as well as flash flood guidance products produced by NWS River Forecast Centers (Hapuarachchi *et al.* 2011, Clark *et al.* 2013, Gourley *et al.* 2016). Recommended actions for those under a flash flood warning include moving to higher ground and avoiding flooded basements (NOAA 2020b). However, public responses to flood warnings are complex and contextual, complicating the warning process (Morss, Mulder, *et al.* 2016).

Many climatological studies have been devoted to individual hazards posed by TCs, but few have examined the intersection of multiple hazards, such as simultaneous and collocated tornadoes and flash floods (TORFFs). When a location is warned for a flash flood and tornado simultaneously, it provides a unique challenge to the public. Most protective actions during flood events usually include moving to higher ground or an upper floor of a building (NOAA 2020b);

however, this is the opposite of the procedure recommended for tornado warnings, which includes moving to the lowest level of a building (NOAA 2020a). These contradicting precautions may cause confusion among people exposed to these hazards simultaneously, forcing them to put themselves in greater risk towards one hazard to protect themselves from the other. The wide variety of TC-related hazards is poorly understood by the general public (Zhang *et al.* 2004, Dueñas-Osorio *et al.* 2012, Senkbeil *et al.* 2018) and such misunderstandings may exacerbate TORFF-related confusion within TCs.

TORFFs are an emerging area of atmospheric hazards research. Rogash and Smith (2000) performed a case study of TORFF events that occurred in March of 1997 in eastern Arkansas and western Tennessee, in which cell training occurred in an area of enhanced low-level wind shear, creating an environment conducive to both flooding and tornadoes (Rogash and Smith 2000). Rogash and Racy (2002) identified meteorological conditions associated with TORFFs, including a moist, unstable airmass and nearby surface boundary that serves as convective forcing (Rogash and Racy 2002). More recently, Nielsen et al. (2015) produced a climatology of TORFF events in the U.S. between the years 2008 and 2014, finding TORFFs to be geographically most common in the middle and lower Mississippi River valley. Using radar data, the authors found that 11% of verified TORFF occurrences in their study were from TCs (Nielsen *et al.* 2015).

In this study, we expand upon current knowledge of TORFF warnings by identifying patterns of TC TORFF warning occurrence across many TCs. While several studies have examined TC tornadoes and extreme TC precipitation individually, this study is the first to focus on the intersection of these hazards in TC environments. We have three research questions:

- What are typical durations, areas, and locations of TC TORFF warnings?

- How do the locations of TC TORFF warnings compare to the locations of TC tornadoes?
- Is TC TORFF warning production affected by TC intensity, translational velocity, or landfall coast?

2.3 Data and Methods

We created a dataset of TORFF warnings associated with TCs from 2008–2018. Using HURDAT2, we identified all TCs that made landfall in the contiguous U.S. during the period at tropical depression strength or greater. HURDAT2 is a database maintained by the National Hurricane Center that provides data on TC location and intensity every six hours during the TC life cycle. We interpolated TC location, intensity, and translational velocity between these six-hourly observations to an hourly scale using a smoothing spline developed by Elsner and Jagger (2013). As in Nielsen *et al*. (2015), we chose to begin the study period in 2008 because the NWS began issuing storm-based warnings for tornadoes and flash floods in 2007 (Nielsen *et al.* 2015). A total of 32 TCs were identified in this manner.

For each of these TCs, tornado and flash flood warnings were obtained from the Iowa Environmental Mesonet Geographic Information System (IEMGIS) archive, found at https://mesonet.agron.iastate.edu/GIS/. We used warnings issued by each NWS office when any part of its county warning area (CWA) was within 500 km of the TC center, the distance used by Barlow (2011) to identify TC precipitation, from the times of landfall to extratropical transition, as defined by the HURDAT2 database for each TC. We identified TORFF warnings by conducting a spatial intersection of tornado warnings with concurrent flash flood warnings using ArcGIS 10.7, excluding any pair of tornado and flash flood warnings that did not overlap both spatially and temporally. While these storm-based warning polygons are all categorized as

‘NEW’ status in the IEMGIS archive, we did take early cancellation severe weather statements into account when determining temporal overlap between tornado and flash flood warnings. Further discussion of storm based warnings and severe weather statements used to update these warnings can be found in Harrison and Karstens (2017). Next, we used the TORFF warning polygons and TC track shapefiles to determine TORFF warning characteristics. We calculated the length of time the tornado warning and the flash flood warnings were valid concurrently (TORFF warning duration), the size of the area in which the tornado warning and flash flood warning overlapped (TORFF warning area), and the distance from each TORFF warning centroid to the coastline. Finally, we determined the location of the TORFF warning centroids relative to TC center. We accomplished this by calculating the distance from each TORFF warning centroid to the location of the TC center when the TORFF warning began. We then measured the angle between the TORFF warning centroid and the TC center with 0° representing the direction of TC motion, and again with 0° representing due north. We analyzed these TORFF warning characteristics using descriptive statistics and bivariate analyses.

Then, we examined characteristics of the TCs that produced the TORFF warnings, including TC landfall intensity, translational velocity, and landfall coastline. Maximum sustained wind speed at landfall was used as a measure of TC landfall intensity. Translational velocity was measured by calculating the average hourly forward speed in knots from the time the TC made landfall until its extratropical transition, thus providing a mean translational velocity while organized over land. As in determining TORFF warnings, we used times of TC landfall and extratropical transition listed in HURDAT2 for this purpose. Elsner and Jagger (2013) provide further detail on interpolating hourly forward speed from six-hourly locations in HURDAT2. The landfall location information was used to create a binary landfall coastline variable, which was assigned a value of 1 if the TC made its first landfall on the contiguous U.S. on the Gulf Coast, and 0 if it made its first landfall on the Atlantic Coast. The southernmost mainland point in the state of Florida was used to divide Gulf Coast from Atlantic Coast.

We ranked the 32 TCs in the dataset by the number of TORFF warnings associated with them and separated the TCs into three categories based on their TORFF warning production: "Active" (n = 9), "Marginal" (n = 10), and "None" (n = 13). The "None" category contains all TCs that had no TORFF warnings associated with them, and the other groups were created to split the remaining TCs approximately in half, as well as to separate TCs like Harvey (2017) and Gustav (2008), which produced many TORFF warnings, from TCs that produced only a few. Because our interest is in the effect that TC characteristics have on TORFF warning production, an ordinal variable, we tested whether landfall intensity, translational velocity, and landfall coastline had the same effect on each TORFF warning production category. The effect of all three variables on TORFF warning production violated the proportional odds assumption (α = 0.05). Thus, rather than an ordinal logistic regression, we performed two binomial logistic regressions on the set of TCs with TORFF warning production being the dependent variable. The first regression tested for differences between those TCs that produced TORFF warnings and those that did not. Thus, the two groups of the dependent variable were "None," which was the reference category, and a second group that combined the "Marginal" and "Active" groups. The second regression tested for differences between those TCs that were associated with few TORFFs to those associated with many. Thus, the two groups were "Marginal" and "Active," with the "Marginal" group as the reference category. The independent variables for these regressions were landfall intensity, translational velocity, and landfall coastline.

2.4 Results

2.4.1 TORFF warning descriptive statistics

We identified 619 TORFF warnings in the study period. The number of TORFF warnings produced by a given TC varied substantially (Table 2.1): Hurricane Harvey (2017) produced 209 TORFF warnings and Gustav (2008) produced 113 TORFF warnings, while 13 other TCs did not produce any. The 32 TCs in the study period produced a mean of 19 and a median of 3.5 TORFF warnings. Of the 19 TCs that did produce at least one TORFF warning, the mean number of TORFFs per TC was 32.6, and the median was 12 TORFF warnings. Since Harvey and Gustav accounted for such a large proportion (52%) of the 619 total TORFF warnings, we present descriptive statistics of TORFF warning attributes both including (*n* = 619) and excluding (*n* = 297) the TORFF warnings from these two TCs. Geographically, TORFF warnings were most common in the central and western Gulf Coast, particularly in the states of Texas, Louisiana, and Mississippi (Figure 2.1). However, they occurred as far northeast as Connecticut and as far inland as Tennessee. The influence of Harvey (2017) and Gustav (2008) is apparent along the Gulf Coast: the red dots clustered primarily in Texas and Louisiana represent TORFF warnings produced by these two TCs.

2.4.2 TORFF warning area, duration, and spatial patterns

The duration of TORFF warnings, or the temporal overlap of intersecting tornado and flash flood warnings, varied from a minimum of one minute to a maximum of 65 minutes. Both mean and median durations were 27.0 minutes, although these values increase slightly to 28.9 and 29.0, respectively, when excluding Harvey (2017) and Gustav (2008) (Table 2.2). The distribution of duration values is nearly normal, with most (71.0%) TORFF warnings lasting between 15 and 50 minutes (Figure 2.2A).

Table 2.1. The 32 TCs in the dataset, including TC characteristics, number of TORFF warnings produced, and TORFF warning production category.

TC (year)	Maximum wind speed at landfall (knots)	Translational velocity (knots)	Landfall coast (state)	TORFF warnings	Category
Harvey (2017)	115	5.49	Gulf (Texas)	209	Active
Gustav (2008)	90	7.56	Gulf (Louisiana)	113	Active
Florence (2018)	80	7.19	Atlantic (North Carolina)	62	Active
Isaac (2012)	70	8.45	Gulf (Louisiana)	59	Active
Lee (2011)	40	3.62	Gulf (Louisiana)	35	Active
Fay (2008)	50	5.94	Gulf (Florida)	27	Active
Irma (2017)	115	13.44	Gulf (Florida)	23	Active
Bill (2015)	50	9.22	Gulf (Texas)	17	Active
Cindy (2017)	45	15.72	Gulf (Louisiana)	16	Active
Ike (2008)	95	19.52	Gulf (Texas)	12	Marginal
Irene (2011)	75	16.96	Atlantic (North Carolina)	11	Marginal
Michael (2018)	140	18.66	Gulf (Florida)	8	Marginal
Matthew (2016)	75	13.57	Atlantic (South Carolina)	6	Marginal
Hanna (2008)	60	25.95	Atlantic (South Carolina)	5	Marginal
Dolly (2008)	75	13.57	Gulf (Texas)	4	Marginal
Gordon (2018)	45	10.68	Gulf (Mississippi)	4	Marginal
Nate (2017)	75	18.88	Gulf (Louisiana)	3	Marginal
Hermine (2016)	70	18.58	Gulf (Florida)	3	Marginal
Beryl (2012)	55	8.19	Atlantic (Florida)	2	Marginal

Table 2.1 continued.

TC (year)	Maximum wind speed at landfall (knots)	Translational velocity (knots)	Landfall coast (state)	TORFF warnings	Category
Edouard (2008)	55	9.96	Gulf (Texas)	0	None
Claudette (2009)	40	13.95	Gulf (Florida)	0	None
Bonnie (2010)	35	14.37	Atlantic (Florida)	0	None
Don (2011)	30	13.49	Gulf (Texas)	0	None
Debby (2012)	35	10.15	Gulf (Florida)	0	None
Andrea (2013)	50	20.80	Gulf (Florida)	0	None
Arthur (2014)	85	22.61	Atlantic (North Carolina)	0	None
Ana (2015)	40	8.26	Atlantic (South Carolina)	0	None
Bonnie (2016)	30	6.08	Atlantic (South Carolina)	0	None
Colin (2016)	45	32.12	Gulf (Florida)	0	None
Julia (2016)	30	5.90	Atlantic (Florida)	0	None
Emily (2017)	50	10.16	Gulf (Florida)	0	None
Alberto (2018)	40	14.57	Gulf (Florida)	0	None

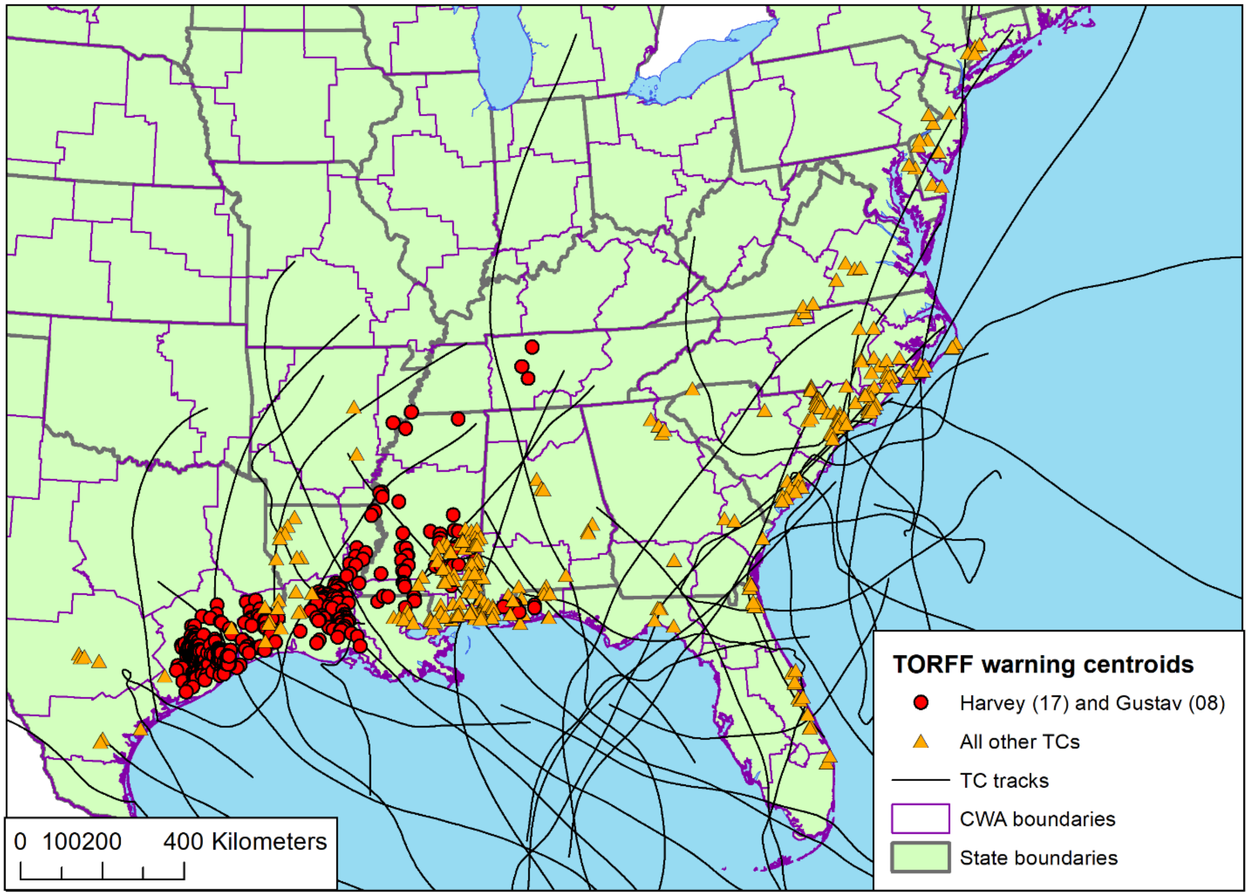

Figure 2.1. Locations of TORFF warning centroids.

Table 2.2. Attributes of TCTORFF warnings.

Attribute	**Mean**	**Standard deviation**	**Median**	**Interquartile Range**
Duration in min (excluding Harvey and Gustav)	27.0 (28.9)	12.7 (13.6)	27.0 (29.0)	16.0 (16.0)
Area in km^2 (excluding Harvey and Gustav)	508.9 (579.4)	588.4 (692.8)	327.0 (397.0)	552.5 (566.6)
Distance from coastline in km (excluding Harvey and Gustav)	86.3 (77.9)	89.2 (86.2)	64.5 (42.6)	87.4 (91.7)
Distance from TC center in km (excluding Harvey and Gustav)	281.8 (286.7)	109.6 (119.8)	263.0 (263.8)	152.7 (125.7)

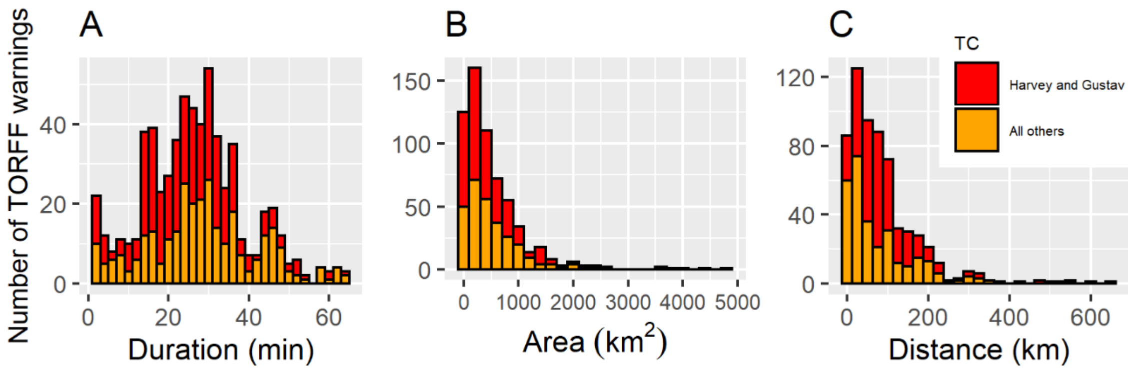

Figure 2.2. Histograms of (A) TORFF warning durations, (B) TORFF warning areas, and (C) TORFF warning centroid distances from coastline.

Spatial metrics of TORFF warnings exhibited much different distributions, with both area (Figure 2.2B) and distance from coastline (Figure 2.2C) exhibiting strong positive skewness. As such, the mean values of both these metrics are much higher than their respective median values (Table 2.2). Nearly all (96.9%) TORFF warnings were less than 2000 km^2 in area, and 91.0% were within 200 km of the coastline. The influence of TORFF warnings from Harvey (2017) and Gustav (2008) decreases (increases) central tendency statistics of area (distance from coastline), suggesting that TORFF warnings from these TCs tended to be smaller and further from the coast than those from the other 17 TCs.

TORFF warnings occurred in all four quadrants of the TC relative to its motion. The right back quadrant (90° < angle < 180° in Figure 2.3A) was the most common motion-relative quadrant for TORFF warnings, containing 43.1% of TORFF warning centroids, followed by the right front quadrant (0° < angle < 90°; 25.5%), and the left front quadrant (270° < angle < 360°; 22.3%). The left back quadrant (180° < angle < 270°) was the least common motion-relative quadrant for TORFF warnings, containing 9.0% of centroids.

Nearly all centroids were located east of the TC center relative to due north (Figure 2.3B), with 70.3% of centroids northeast of TC center (0° < angle < 90), and 28.4% southeast of TC center (90° < angle < 180°). Centroids in the northeast quadrant were typically within 200 km of the TC center, while centroids in the southeast quadrant were nearly all beyond 200 km of TC center (Figure 2.3B). For TORFF centroids in the northeast quadrant, the mean distance from TC center was 254.5 km, and the median distance was 234.5 km. The mean distance from TC center for centroids in the southeast quadrant was 346.2 km, and the median distance was 353.6 km. A Mann-Whitney test revealed that the distances from TC center were significantly different between northeast quadrant centroids and southeast quadrant centroids ($\alpha = 0.01$).

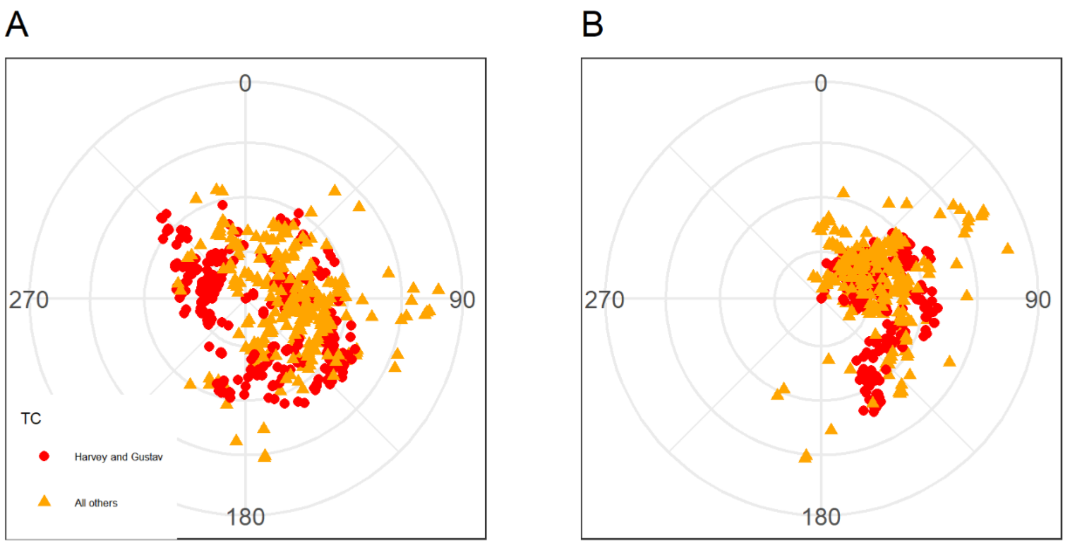

Figure 2.3. Plots of TORFF warning centroids relative to (A) TC direction and (B) compass north.

TORFF warnings produced by Harvey (2017) and Gustav (2008) influenced these patterns in TC-relative locations (Figure 2.3A) substantially. Excluding the TORFF warnings from these TCs increases the proportion of TORFF warning centroids in the right back TC quadrant from 43.1% to 51.2% and in the right front quadrant from 25.5% to 34.3%. Only 11.8% (2.7%) of TORFF warning centroids in the left front (left back) quadrant of TCs other than Harvey and Gustav; a substantial drop from 22.3% (9.0%). This shows that the two most active TCs in terms of TORFF warning production exhibited very different TC-relative spatial distributions of TORFF warnings than other TCs by producing more TORFF warnings in their left front and left back quadrants than other TCs in the study period. We examine these patterns further in the Discussion section.

Compass-relative TORFF warning distributions (Figure 2.3B) shift as well when excluding Harvey and Gustav, although the differences are not quite as pronounced. The northeast quadrant accounted for 75.1% of the total TORFF warnings when excluding these two TCs, an increase from 70.3% when including them, and the southeast quadrant encompassed for 22.2% of non-Harvey, non-Gustav TORFF warnings, compared to 28.4% when including them.

2.4.3 TORFF warning production rates

TCs in the Active and Marginal categories exhibited landfall intensities with higher central tendency values than the None category, while TCs in the Active category exhibited translational velocities with lower central tendency values than the Marginal and None categories (Table 2.3). Likewise, a greater proportion of Active TCs made landfall on the Gulf Coast than for the Marginal and None categories. We used the first binomial logistic regression model to determine differences in the characteristics of TCs that produced TORFF warnings and those that did not (Table 2.4). The intensity variable was significant ($\alpha = 0.01$) for this regression,

Table 2.3. Central tendency characteristics for each category of TORFF warning production.

Category	**Landfall intensity (wind speed in knots)**	**Mean Translational Velocity at Landfall (knots)**	**Landfall Coast**
Active (mean)	72.8	8.5	8 Gulf Coast
Active (median)	70.0	7.6	1 Atlantic Coast
Marginal (mean)	76.5	16.0	6 Gulf Coast
Marginal (median)	75.0	17.8	4 Atlantic Coast
None (mean)	43.5	14.0	8 Gulf Coast
None (median)	40.0	13.5	5 Atlantic Coast

Table 2.4. Results of a binomial logistic regression of TCs in the "None" category, compared with TCs in the "Marginal" and "Active" categories, with "None" as the reference category. Significance at the α = 0.05 level is denoted by an asterisk (*), while significance at the α = 0.01 level is denoted by a double asterisk (**).

	Maximum Sustained Wind Speed at Landfall	**Mean Translational Velocity at Landfall**	**Gulf Coast Landfall**	**Intercept**
Coefficient	0.114** (0.034 – 0.194)	–0.143 (–0.329 – 0.043)	0.816 (–1.367 – 2.999)	–4.501* (–8.850 – –0.152)
Odds ratio	1.121 (1.035 – 1.214)	0.866 (0.720 – 1.044)	2.263 (0.255 – 20.065)	n/a

indicating that TC intensity effectively differentiated between TCs that did or did not produce TORFF warnings. In terms of odds ratios, each increase of one knot in maximum sustained wind speed at landfall made a TC 1.121 times more likely to be categorized in the “Marginal” or “Active” categories as opposed to the “None” category. To assess model fit for this regression, we used the Hosmer-Lemeshow test since two of the three explanatory variables were continuous in nature. We performed this test four times, adjusting the number of bins from 7 to 10. None of these four bin numbers yielded a significant result at the $\alpha = 0.05$ level, suggesting that goodness-of-fit was sufficient. We also inspected Pearson residual plots and performed Bonferroni-corrected outlier tests for the 32 TCs in the regression. These methods confirmed that none of the 32 TCs in the analysis would be classified as outliers.

We used the second binomial logistic regression model to determine differences in the characteristics of TCs that were “Marginal” or “Active” TORFF warning producers (Table 2.5). The translational velocity variable was significant ($\alpha = 0.05$) for this regression, indicating that TC translational velocity effectively differentiated between TCs in the “Marginal” and “Active” categories. In terms of odds ratios, each increase of one knot in translational velocity after landfall made a TC 0.666 times as likely to be in the “Active” category than in the “Marginal” category. Once again, we used the Hosmer-Lemeshow test to assess model fit. Since this regression involved a smaller number of TCs, we repeated the test with bin numbers ranging from 5 to 8. None of these test results were significant ($\alpha = 0.05$), confirming that model fit was sufficient. Pearson residual plots and Bonferroni-corrected outlier tests did not show any of the 19 TCs as outliers for this regression.

Table 2.5. Results of a binomial logistic regression of TCs in the "Marginal" and "Active" categories, with "Marginal" as the reference category. Significance at the $\alpha = 0.05$ level is denoted by an asterisk (*).

	Maximum Sustained Wind Speed at Landfall	**Mean Translational Velocity at Landfall**	**Gulf Coast Landfall**	**Intercept**
Coefficient	0.013 (–0.038 – 0.064)	–0.406* (–0.765 – –0.047)	2.219 (–1.009 – 5.447)	2.037 (–2.442 – 6.516)
Odds ratio	1.013 (0.963 – 1.066)	0.666 (0.463 – 0.954)	9.201 (0.365 – 232.061)	n/a

2.5 Discussion

2.5.1 Global Considerations

This study provides new knowledge on the occurrence of TORFF warnings associated with TCs, and our results make for useful comparisons to prior research on NWS warning patterns (Harrison and Karstens 2017), TORFFs (Nielsen *et al.* 2015), and TC tornadoes (McCaul 1991, Verbout *et al.* 2007, Schultz and Cecil 2009, Moore and Dixon 2011, Edwards 2012, Moore *et al.* 2017). Additionally, while we focused on TORFF warning events in the contiguous U.S., this work has international implications. Simultaneous and concurrent tornadoes and flash floods associated with TCs are likely a global phenomenon, much like TCs themselves. The Caribbean islands, particularly Cuba, are vulnerable to TC tornadoes (Edwards 2012), and several studies have been devoted to TC tornadoes in East Asia (Mashiko *et al.* 2009, Sueki and Niino 2016, Bai *et al.* 2017). Torrential TC rainfall and associated flooding has been observed globally as well (Kostaschuk *et al.* 2001, Reason and Keibel 2004, Terry *et al.* 2008, Villarini and Denniston 2016, Khouakhi *et al.* 2017). Using the methods presented above, we identified one TORFF warning associated with Hurricane Irene (2011) on the island of Puerto Rico, which is prone to flooding events from TCs (Hernandez Ayala *et al.* 2017). TC TORFF occurrence in locations outside the U.S. is an avenue for future research, although inconsistencies in meteorological records and warning procedures represent a substantial challenge.

2.5.2 Geographic Locations of TC TORFF warnings

Geographically, we found that TC TORFF warnings were most common in regions along the Gulf and Atlantic Coasts (Figure 2.1), which are also the most active regions for TC tornadoes (Schultz and Cecil 2009, Moore *et al.* 2017). TORFF warnings were most dense in the central and western Gulf Coast and the Carolinas, although this pattern is affected by the tracks of the most prolific TORFF warning producing TCs. The spatial distribution of TC TORFF warnings in this study is in line with Nielsen et al. (2015), who identified many TORFF warnings along the Gulf Coast in the late summer and early fall months that the authors correctly noted were likely caused by TCs (Nielsen *et al.* 2015). The geographic centroid of all TORFF warning occurrences identified by Nielsen et al. (2015) was in southern Missouri, and our results suggest that TORFF warnings caused by TCs moved this centroid to the south and east.

2.5.3 Comparing TC TORFF warnings to TC tornadoes

TC TORFF warnings occur in similar locations as TC tornadoes (Schultz and Cecil 2009, Moore *et al.* 2017), with the Gulf Coast, Florida, and southern and middle Atlantic Coasts being active regions for both phenomena. However, TC TORFF warnings observed in this study (Figure 2.1) appear to be proportionally less common in Florida and the Atlantic Coast than TC tornadoes (Moore et al., 2017, Figure 2; Schultz and Cecil, 2009, Figure 1). TC TORFF warnings are also more likely to occur nearer to the coastline than the TC tornadoes observed in Schultz and Cecil (2009) and Moore et al. (2017) (Table 2.6). A likely explanation for this is the location of TC-induced flash flood warnings relative to the coastline. Since the warm waters of the Gulf of Mexico and Atlantic Ocean provide a source of moisture for extreme precipitation rates, flash flood warnings associated with TCs are more likely to be confined to regions near the coastline than TC tornado warnings and TC tornadoes, hence the greater proportion of TC TORFF warnings having occurred within 100 km of the coastline than TC tornadoes.

Previous research has established that TC tornadoes most commonly occur in the right-front quadrant, relative to TC motion (Schultz and Cecil 2009, Edwards 2012). However, we found that TC TORFF warnings were most common in the right-back quadrant, with the right-

Table 2.6 Comparison of TC TORFF warnings in this study and TC tornado warnings in prior research in terms of distance from coastline.

Study (phenomena)	**Percentage occurring < 100 km from coastline**	**Percentage occurring between 100 and 200 km from coastline**	**Percentage occurring between 200 and 300 km from coastline**	**Percentage occurring > 300 km from coastline**
Schultz and Cecil (2009) (TC tornadoes, 1950–2007, *n* = 1767)	61.69	17.15	10.07	11.09
Moore et al. (2017) (TC tornadoes, 1995–2015, *n* = 1285)	49.34	20.39	15.80	14.47

front and left-front quadrants exhibiting a near equal amount of TORFF warnings (Figure 2.3a). We attribute this to two factors: 1) precipitation residence time over the affected region, and 2) atypical translational motion of TCs that are the most active TORFF warning producers. The right-back quadrant is still a common region for TC tornado occurrence, although not to the extent of the right-front quadrant (Schultz and Cecil 2009, Edwards 2012). Meanwhile, regions in the right-back quadrant of the TC have likely been exposed to heavy rainfall while they were affected by the TC's right-front quadrant, making it more likely that flash flood guidance criteria are met and flash flood warnings are issued. As such, while the right-back quadrant may not be the most active for TC tornadoes, it is favorable for overlapping and concurrent tornado and flash flood warnings, and thus TORFF warnings.

The proportion of TORFF warnings in the left-front quadrant relative to TC motion (Figure 3a) is a surprising finding of this study. However, most of these TORFF warnings are attributable to Hurricane Harvey (2017), and TORFF warnings in the left-front quadrant were much less common among the other 31 TCs in this study. Of the 138 TORFF warnings in the left-front quadrant, 103 (74.64%) were associated with Harvey (2017). Immediately before and after landfall in southeast Texas, Harvey moved to the northwest, producing TORFF warnings in its right-front quadrant in east Texas (Figure 2.4). Then, Harvey stalled and reversed course, moving back out over the Gulf of Mexico. As the TC drifted to the southeast, the orientation of the TORFF warnings that continued to occur in east Texas and southwest Louisiana was changed from Harvey's right-front to its left-front quadrant. Verbout et al. (2007) and Edwards (2012) discuss tornadoes produced by Hurricane Beulah (1967), which, like Harvey, made landfall in southeast Texas and moved erratically afterwards, producing tornadoes in its left half, relative to TC motion (Verbout *et al.* 2007, Edwards 2012).

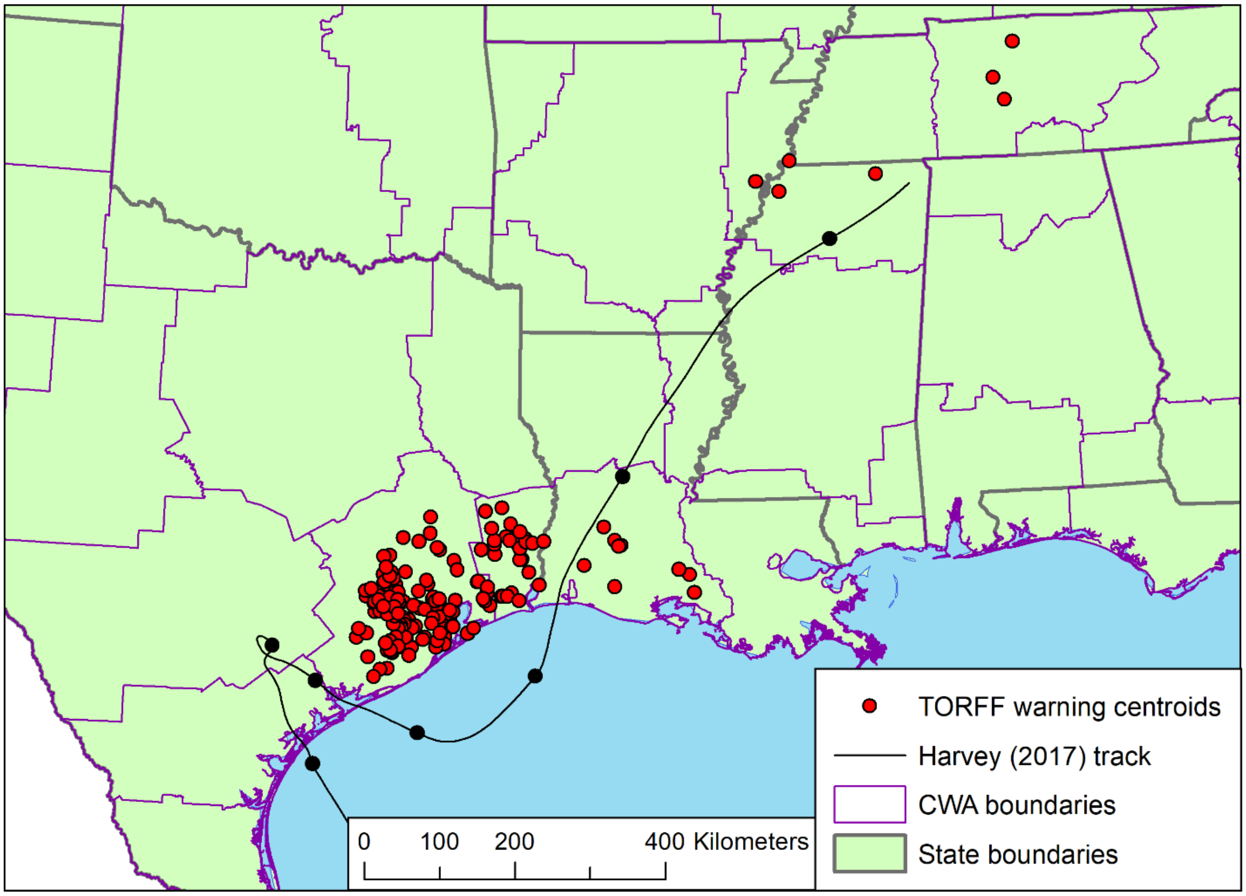

Figure 2.4. TORFF warning centroids produced by Hurricane Harvey (2017).

Plotting TORFF warnings relative to due north (Figure 2.3B) shows a strong pattern of occurrence almost exclusively east of TC center. This fits well with the findings of Schultz and Cecil (2009) and Moore et al. (2017) on TC tornadoes. TORFF warnings in the southeast quadrant are significantly farther from TC center than in the northeast quadrant. This may be because outer rain band convection in the northeast quadrant tends to affect regions that have not been exposed to heavy rainfall, so the only regions experiencing heavy precipitation, and thus risk of flash flooding, are in the TC's inner core. On the other hand, regions southeast of the TC center are more likely to have received high precipitation amounts as the TC moved through, and thus guidance thresholds for flash flood warning issuance are more easily met here by convection in the outer bands. Additionally, most TCs in the dataset moved generally northward during and after landfall (Figure 2.1), so the easterly half of these TCs exhibited southerly low-level flow, which likely enhanced moisture advection from the Gulf of Mexico or Atlantic Ocean.

Finally, it is important to note that TC tornado studies tend to examine *observed* TC tornadoes rather than TC tornado *warnings*, and TC tornado warnings are difficult to verify since the widespread damage caused by other TC hazards (flooding, surge, straight-line winds, etc.) may mask TC tornado damage (Edwards 2012). As such, there may be systematic differences in false alarm rates for TC tornadoes that are complex and difficult to account for.

2.5.4 Operational Considerations

The mean TORFF warning area in this study was 508.9 km^2 (Table 2.2), which is about half the mean tornado warning area of 999 km^2 found by Harrison and Karstens (2016). Since we defined a TORFF warning spatially as the geographic overlap between simultaneous tornado and flash flood warnings, this was expected. However, some TC TORFF warnings were much larger than 999 km^2 in area, suggesting that the entire corresponding tornado warning overlapped a valid flash flood warning. Likewise, the mean TC TORFF warning duration of 27.0 minutes (Table 2.2) is substantially shorter than the mean tornado warning duration of 38 minutes identified by Harrison and Karstens (2016), although some TC TORFF warnings had durations longer than 38 minutes and likely consisted of complete temporal overlap between their respective tornado and flash flood warnings.

Nielsen et al. (2015) found gradients in TORFF warning occurrence along CWA boundaries, signifying possible differences in warning procedures between NWS offices. This appears to be the case in our study as well, with abrupt breaks in TORFF warning occurrence along CWA boundaries in Louisiana, Mississippi, Alabama, and Texas (Figure 2.1). While TORFF warnings clearly cluster in certain regions of a TC (Figure 2.3), NWS forecasters may have differing tendencies in warning issuance, and flash flood guidance products may vary in quality as well (Clark *et al.* 2013, Gourley *et al.* 2016). From a societal perspective, coastal cities in the southeastern U.S., such as New Orleans, Louisiana; Baton Rouge, Louisiana; and Charleston, South Carolina, have been identified as particularly vulnerable to environmental hazards (Borden *et al.* 2007), and our results show that TORFF warnings are common in these areas.

2.5.5 TC characteristics affecting TORFF warning production rates

The number of TORFF warnings produced by a given TC can vary substantially (Table 2.1). We found that an increase in TC intensity was associated with an increase in likelihood that the TC would produce at least one TORFF warning (Table 2.4). We also found that a decrease in TC translational velocity was associated with an increase in likelihood that the TC would produce many TORFF warnings, rather than just a few (Table 2.5). In other words, intense TCs were likely to produce at least a few TORFF warnings, while intense and slow-moving TCs were likely to produce many TORFF warnings. These patterns are evident in descriptive statistics of each TORFF warning production category (Table 2.3). The four most prolific TCs in terms of TORFF warning production each had wind speeds at landfall of 70 knots or greater (hurricane strength) and post-landfall translational velocities of 8.5 knots or less (Table 2.1). These findings are in line with prior research, which has found that more intense TCs are more likely to produce tornado outbreaks (McCaul 1991, Verbout *et al.* 2007, Moore and Dixon 2011), and that slower-moving TCs are more likely to produce extreme local precipitation amounts (Konrad *et al.* 2002).

2.5.6 Study Limitations

The main limitation to this study is the number of TCs we examined (32), which is smaller than an ideal sample size. The two major implications of this limitation are the relative influence of the TCs that produced the most TORFF warnings, as well as possible underestimation of the explanatory power of the independent variables listed in Tables 2.4 and 2.5. Hurricanes Harvey (2017) and Gustav (2008) accounted for just over half of TORFF warnings that we identified in this study (Table 2.1), so TORFF warning characteristics such as geographic (Figure 2.1) and TC-relative (Figure 2.3) locations are strongly influenced by these TCs. A few select TCs have been found to produce an exceptionally large number of tornadoes (Edwards 2012), so this pattern is certainly consistent with relevant studies. While we did find significance in some of the regression coefficients in Tables 4 and 5, a small sample size makes for an increased probability of a Type II error, in which true significance in an explanatory variable is left unidentified. This could be the case for the Gulf Coast landfall variable for membership in the “Active” TORFF warning production category, since nearly all TCs in the “Active” category made landfall on the Gulf Coast. These Gulf Coast-landfalling TCs tend to produce more tornadoes since their right-front quadrants are located over land (Novlan and Gray 1974), so identification of a similar pattern in TORFF warnings would also be in line with established findings. Future TC TORFF warning climatology research may shed more light on this pattern.

2.6 Conclusions

In this study, we examined TORFF warnings—complex and dangerous meteorological hazards—that were associated with TCs in the southeastern U.S. We identified a total of 619 TORFF warning occurrences occurring in 19 of the 32 TCs in the study period. Most TORFF warnings occurred in the TC-prone Gulf and Atlantic coastal regions, and most frequently in the states of Texas, Louisiana, and Mississippi. While TORFF warnings were located in all four TC quadrants relative to TC motion, they were most common in the right-back quadrant, and nearly all were east of the TC center. TORFF warnings tended to occur nearer to the coastline than TC tornadoes, likely since the waters of the Atlantic Ocean and Gulf of Mexico provide a moisture source for flood-inducing precipitation. TORFF warnings were also relatively more common in the TC's right-back quadrant than TC tornadoes. We found that the number of TORFF warnings associated with a given TC varied substantially, with Hurricanes Harvey (2017) and Gustav (2008) each producing over 100 TORFF warnings, while 13 TCs did not produce any TORFF warnings. Using logistic regressions, we determined that more intense TCs were more likely to produce at least one TORFF warning, while slower-moving TCs were more likely to produce many TORFF warnings. There are several avenues for future research on this topic, including TC TORFF warning verification, mesoscale characteristics, and public response.

Chapter 3

Precipitation and synoptic weather types on hazardous weather days in the Southeastern United States

As of 9 March 2021, a version of this study is in revision for *Theoretical and Applied Climatology*. The following chapter is adapted from this manuscript after having undergone a round of peer review revisions. I am lead author on this manuscript, and Kelsey Ellis is a coauthor. Thus, I use “we” in this chapter, in recognition of these contributions.

3.1 Abstract

As Earth’s climate warms, global precipitation regimes will change. The role in which precipitation poses a hazard to human societies is a key factor in anticipating the consequences of Earth’s changing climate. The southeastern U.S. faces a unique variety of hydrometeorological hazards, including severe convective weather, floods, tropical cyclones, and winter storms. The purpose of this research is to identify the role of hazardous weather days (HWDs) in the precipitation regime of the Southeast and the synoptic weather types associated with HWDs in this region. We use warnings issued by the National Weather Service (NWS) to identify HWDs, for which we quantify the daily precipitation, and determine the dominant synoptic weather type on using the Spatial Synoptic Classification (SSC) system. We find two geographic maxima of precipitation on HWDs in the southeastern U.S.: one in the lower Mississippi Valley, and another in the Carolinas. We also find that the proportion of precipitation that falls on HWDs tends to be highest on Transition SSC days, associated with changing airmasses and frontal boundaries. However, stations in the lower Mississippi Valley (Carolinas) experience a relatively high amount of precipitation on Moist Moderate (Moist Tropical) days, and seasonally during spring (summer). Results from this study can be paired with SSC trend analyses to anticipate changes in the nature of hydrometeorological hazards in the southeastern U.S. Additionally, the distinct precipitation regimes within the study area may each experience differing effects in a changing climate.

3.2 Background

3.2.1 Introduction

Detecting and quantifying trends in the frequency of hydrometeorological hazards is an important goal of climatological research, especially as the global climate changes; however, determining long-term trends and patterns in frequency is difficult. Issues emerge because of discrepancies, biases, and systematic errors in event records and limits to computing power and model resolution of complex mesoscale events (Kunkel *et al.* 2013). A common approach to this challenge is examining trends in synoptic weather types that are associated with hazardous mesoscale events because these events can be proxied by model downscaling of synoptic-scale patterns (Trapp *et al.* 2011). Synoptic weather typing is a surface based classification of ambient weather conditions into categories (Sheridan 2002) and is a popular method to distill complex atmospheric processes into similar groups. This method is particularly advantageous in regions that frequently experience a diverse suite of meteorological events, such as the Southeastern U.S.

The southeastern U.S. (hereafter SEUS), defined here as 25 NWS county warning areas (CWAs) predominantly east of the Mississippi River and south of the Ohio and Potomac rivers, experiences many hazardous hydrometeorological events, including tornadoes, severe thunderstorms, tropical cyclones, extreme rainfall, snow, and ice storms. Previous studies have identified the risks that each of these hazards pose to the region and throughout the country. For example, Gensini et al. (2014) determined that environments favorable for severe weather are likely to increase in frequency in future decades in the SEUS, while Skeeter et al. (2019) found a similar increasing trend for intense precipitation events in the region. Results from these studies allow for conclusions on how each type of event contributes to the hazard profile of the SEUS.

More broadly, research on precipitation and its hazards to society produce knowledge on climatological baselines, extreme events, and societal effects (Trenberth *et al.* 2003).

The goal of this study is to identify the role of hazardous weather days (HWDs) in the precipitation regime of the SEUS and to determine the synoptic weather type(s) associated with precipitation on HWDs. The results from this research will determine which synoptic weather types are associated with hydrometeorologically hazardous weather events in the study area. Additionally, future research on synoptic weather type trends can use these findings to draw conclusions on the future of hydrometeorological hazards in the region.

3.2.2 Hydrometeorological hazards in the SEUS

Severe convective weather, such as tornadoes, damaging wind, and hail, is perhaps the most common meteorological hazard to the region. Research has shown that the SEUS is an active area for nocturnal tornadoes (Ashley *et al.* 2008a), significant (EF-2–EF-5) tornadoes (Coleman and Dixon 2014), and tornado outbreaks (Fuhrmann *et al.* 2014). Severe hail and wind events also occur frequently in the region (Doswell *et al.* 2005, Allen and Tippett 2015). While historical analysis of these events are possible, they are challenging because of poor record quality and inconsistencies in reporting (Verbout *et al.* 2006, Doswell 2007, Paulikas 2014, Allen and Tippett 2015). However, recent technological advances have made it easier for hazardous events to be observed remotely (Simmons and Sutter 2005, Brotzge and Donner 2013). Because of this inconsistency in reporting practices, some research has focused on synoptic environments conducive for severe convection. These environments have become more common in the SEUS over the past few decades (Gensini and Brooks 2018) and this trend is likely to continue into the 21st century (Diffenbaugh *et al.* 2013, Gensini and Mote 2015).

Tropical cyclones are another threat to the SEUS because they can produce damaging winds (Scheitlin *et al.* 2011) and 100% of a location's average annual precipitation totals in a matter of days (Nogueira and Keim 2010). Tropical cyclones at tropical storm strength (winds > 62 km/h) or greater affect coastal areas from Texas to Virginia every five years or less, on average (Keim *et al.* 2007). Each tropical cyclone presents a unique combination of precipitation-, surge-, and wind-related hazards (Senkbeil and Sheridan 2006). Slow-moving tropical cyclones tend to produce higher precipitation amounts over local areas (i.e., Hurricane Harvey), while large tropical cyclones tend to produce the most precipitation along the length of their paths (Konrad *et al.* 2002). Fatalities from tropical cyclone-induced flooding are common, particularly in coastal areas (Ashley and Ashley 2008b). From 1980–2004, tropical cyclones produced a majority of precipitation accumulation amounts in south Florida but contributed the highest percentage of annual precipitation in the Carolinas (Knight and Davis 2007, Prat and Nelson 2012). The proportion of annual precipitation from tropical cyclones has increased across the SEUS (Knight and Davis 2009) and further increases are anticipated due to increases in sea surface temperatures (Knutson *et al.* 2010, Scoccimarro *et al.* 2014, Villarini, Lavers, *et al.* 2014).

Flash floods are defined as the sudden-onset hazards caused by extreme precipitation over short periods (NOAA NSSL 2021) and occur year-round in the SEUS (Dougherty and Rasmussen 2019). The states of Georgia, Kentucky, North Carolina, Tennessee, and Virginia each averaged ≥ 1 one flash-flood fatality annually from 1959–2005 (Ashley and Ashley 2008b). Flash flooding events that occur concurrently with tornadic events pose another unique hazard to the region (Nielsen *et al.* 2015). Similar to severe convective weather, documentation of flash flood events have historically been limited by population biases in addition to reporting and verification challenges (Herman and Schumacher 2018), and robust, long-term climatologies of flash flood events have had to account for these limitations (Gourley *et al.* 2013, Dougherty and Rasmussen 2019).

Snow, sleet, freezing rain, and other types of winter precipitation are not as common in the SEUS as they are in other parts of the country; however, winter storms can cause major economic losses in the region (Changnon 2007). High elevations of the southern Appalachians experience heavy snow (Perry *et al.* 2010), as do lower elevations farther east (Fuhrmann and Konrad 2013). Much of the region experiences an average of at least one freezing-rain day annually, with higher amounts on the leeward side of the Appalachians where cold air damming causes thermal inversions during the colder months of the year (Changnon and Karl 2003, Houston and Changnon 2007).

Several recent climatological studies have focused on extreme precipitation events in the SEUS (Moore *et al.* 2015, Powell and Keim 2015, Brown *et al.* 2019, Skeeter *et al.* 2019, Brown, Keim, and Black 2020). Examples of these extreme events include the May 2010 flood in Kentucky and Tennessee (Durkee *et al.* 2012, Keim *et al.* 2018), record-breaking precipitation accumulations from hurricanes Harvey (van Oldenborgh *et al.* 2017) and Florence (Reed *et al.* 2020), and the August 2016 flooding event in Louisiana (Wang *et al.* 2016, Brown, Keim, Kappel, *et al.* 2020). Seasonally, extreme precipitation events are more common in spring west of the Appalachians, and during summer east of the Appalachians (Moore *et al.* 2015). On a multidecadal time scale, hourly (Brown *et al.* 2019) and daily (Powell and Keim 2015) precipitation intensity has increased across the SEUS, while >99th percentile two-day accumulation events are increasing in frequency as well (Skeeter *et al.* 2019). This increase in extreme event frequency is expected to continue in a warming climate (Chou *et al.* 2012, Fischer and Knutti 2015).

3.2.3 NWS Warnings

The National Weather Service (NWS) uses hazardous weather warnings to alert the public to take protective action (Pifer and Mogil 1978). Tornadoes (Brotzge and Donner 2013), tropical cyclones (Demuth *et al.* 2012), flash floods (Hapuarachchi *et al.* 2011, Morss, Mulder, *et al.* 2016), and other hazards each have unique warning processes and challenges. For example, tornado detection and associated warning lead time is affected by the amount of information available to forecasters from radars and spotters (Brotzge and Donner 2013). Studies on warnings have a variety of foci, including public differentiation between watches and warnings (Schultz *et al.* 2010, Sherman-Morris 2010, Silver 2015), warning perceptions (Morss and Hayden 2010, Meyer *et al.* 2014), channels of warning receipt (Hammer and Schmidlin 2002, Comstock and Mallonee 2005, Jauernic and Van Den Broeke 2016), and protective actions following receipt (Morss, Demuth, *et al.* 2016, Walters *et al.* 2019). Warning-focused research in the SEUS is most commonly focused on tornadoes (Sherman-Morris 2010, Mason *et al.* 2018, Walters *et al.* 2019, Ellis, Burow, *et al.* 2020) and tropical cyclones (Broad *et al.* 2007, Meyer *et al.* 2014, Morss, Demuth, *et al.* 2016) given the region's climatological risk to these hazards.

An emerging technique in hazardous weather climatologies uses NWS warnings as a variable of interest rather than reports or observations (Bruick and Karstens 2017, Harrison and Karstens 2017, White and Stallins 2017, Naylor and Sexton 2018). For most hazards, the meteorological criteria are consistent across CWAs. However, requisite thresholds for winter storm, ice storm, and flash flood warnings vary geographically to reflect the severity necessary for the phenomena to pose a local hazard, depending on factors such as societal sensitivity to winter weather or local hydrology. One main advantage to this method is that warnings are presumably less prone to population and reporting bias than observational datasets, although local maxima have been observed in or near urban areas and attributed to urban heat islands (Naylor and Sexton 2018) and densely populated areas (White and Stallins 2017).

3.2.4 The Spatial Synoptic Classification

As an alternative to studying trends in hazardous weather observations, researchers have examined climatic-scale changes in synoptic weather types that are conducive to hazardous events. The Spatial Synoptic Classification (SSC) is one method of discretely categorizing calendar days at a given location based on observations of temperature and moisture (Sheridan 2002). There are a total of seven categories corresponding to six different weather types ("Dry Moderate", "Dry Polar", "Dry Tropical", "Moist Moderate", "Moist Polar", and "Moist Tropical"), plus an additional category for days where two different airmasses affect a given location ("Transition") (Sheridan 2002). In the Southeast, the SSC has primarily been used to study heat waves and human vulnerability (Sheridan *et al.* 2009, Sheridan and Kalkstein 2010), urban enhancement of convection (Ashley *et al.* 2012, Bentley *et al.* 2012), and intense precipitation events (Skeeter *et al.* 2019). A major advantage of the SSC system is its utility on multidecadal time scales (Sheridan 2003, Greene *et al.* 2011, Hondula and Davis 2011b, Senkbeil *et al.* 2017). Hazardous weather observations, on the other hand, are less reliable on these long time scales because of population biases and changes in reporting (Kunkel *et al.* 2013, Paulikas 2014). Thus, connecting individual hazardous weather occurrences to predominant SSC types allows for long-term trends in hazardous weather to be observed and projected (Greene *et al.* 2011, Lee 2012, Skeeter *et al.* 2019).

3.2.5 Study Objectives

The objectives of this study are to identify the role of HWDs in the precipitation regime of the SEUS and to identify the synoptic weather types associated with HWDs in the region. Results can be used to guide research on future trends in hazardous weather, particularly those that use synoptic weather classifications. Three main research questions comprise these objectives:

1. How much precipitation falls on HWDs at observation stations in the SEUS, and how does this compare to seasonal and annual precipitation totals at these locations?
2. What synoptic type is responsible for the most HWDs, and what type produces the most precipitation on HWDs?
3. How do seasonal and synoptic patterns of precipitation on HWDs vary geographically throughout the region?

3.3 Data and Methods

We examined precipitation on HWDs from 2009–2018 at 40 observation stations throughout the SEUS (Table 3.1). We selected these stations from 25 NWS CWAs in the mainland U.S. that are predominantly east of the Mississippi River and south of the Ohio and Potomac rivers and located near large population centers. Each station was located at least 80-km from the other selected stations and no more than two stations were selected from the same NWS CWA. For each station, we defined a HWD as a day in which one of the following weather warnings was issued by the NWS or valid at its location: severe thunderstorm, tornado, flash flood, hurricane, tropical storm, ice storm, winter storm, or blizzard. While the NWS issues warnings for many other hazards including heat, high wind, or river flooding, these events are

Table 3.1. Observation stations used in this study.

Station	City	NWS CWA	Station	City	NWS CWA
KBHM	Birmingham, AL	BMX	KBTR	Baton Rouge, LA	LIX
KMGM	Montgomery, AL	BMX	KMSY	New Orleans, LA	LIX
KHSV	Huntsville, AL	HUN	KJAN	Jackson, MS	JAN
KMOB	Mobile, AL	MOB	KTUP	Tupelo, MS	MEG
KGNV	Gainesville, FL	JAX	KCGI	Cape Girardeau, MO	PAH
KJAX	Jacksonville, FL	JAX	KAVL	Asheville, NC	GSP
KMIA	Miami, FL	MFL	KCLT	Charlotte, NC	GSP
KPBI	W. Palm Beach, FL	MFL	KILM	Wilmington, NC	ILM
KMCO	Orlando, FL	MLB	KEWN	Greenville, NC	MHX
KTLH	Tallahassee, FL	TAE	KGSO	Greensboro, NC	RAH
KRSW	Fort Myers, FL	TBW	KRDU	Raleigh/Durham, NC	RAH
KTPA	Tampa, FL	TBW	KCAE	Columbia, SC	CAE
KAGS	Augusta, GA	CAE	KCHS	Charleston, SC	CHS
KSAV	Savannah, GA	CHS	KMEM	Memphis, TN	MEG
KATL	Atlanta, GA	FFC	KCHA	Chattanooga, TN	MRX
KMCN	Macon, GA	FFC	KTYS	Knoxville, TN	MRX
KEVV	Evansville, IN	PAH	KBNA	Nashville, TN	OHX
KJKL	Jackson, KY	JKL	KORF	Norfolk, VA	AKQ
KLEX	Lexington, KY	LKM	KRIC	Richmond, VA	RIC
KSDF	Louisville, KY	LKM	KROA	Roanoke, VA	RNK

either unrelated to precipitation or occur over time scales longer than a few days. Instead, the warnings selected for this study represent mesoscale hydrometeorological hazards that usually occur on timescales of a day or less. Occasionally, more than one of the selected warnings was issued on the same day for these stations. We treated these HWDS no differently than other HWDs with only one warning issued.

We obtained daily precipitation data for the selected stations from the Land-Based Station Data archive maintained by the National Center for Environmental Information and NWS warning data from Iowa State University's Environmental Mesonet archive. The SSC airmass type data were obtained from http://sheridan.geog.kent.edu/ssc3.html. SSC version 3.0 was developed and made available in late 2019, and this is one of the first studies to use this version of the SSC system. Two stations in Table 3.1—Jackson, Kentucky, and Cape Girardeau, Missouri—did not have SSC data available, so we did not use these two stations for the SSC analysis.

For each of the 40 stations, we calculated the amount of precipitation that fell from midnight-to-midnight local time on HWDs and compared it to the total amount of precipitation at that location over the ten-year study period. We then repeated this process for each of the four meteorological seasons—spring (March, April, May), summer (June, July, August), fall (September, October, November), and winter (December, January, and February)—and for each SSC type.

3.4 Results

Spatial patterns are apparent in the amount of precipitation that occurred on HWDs at the 40 stations. The proportion of precipitation on HWDs relative to the total amount of precipitation at that station over the study period varied as well (Figure 3.1). The stations in the southwest portion of the study area received the highest amounts of precipitation on HWDs during the study period (Figure 3.1A). Mobile, AL; Jackson, MS; and Memphis, TN, each received over 450 cm of precipitation on HWDs, equaling over 45 cm per year. Another subtler maximum is located in the Carolinas, from Charleston, SC, north to Greensboro, NC. Stations in this sub-region received ≥ 300 cm of precipitation on HWDs during the study period. Stations that received the lowest precipitation totals on HWDs are in the Appalachians, Georgia, and peninsular Florida. These patterns are distinct from the number of HWDs at the study stations (appendix Table A1 and Figure A1).

Similar to the total amount of precipitation on HWDs, the proportion of precipitation falling on HWDs exhibits maxima in the lower Mississippi Valley, and the Carolinas (Figure 3.1B). Precipitation on HWDs at these stations accounted for over 27% of the total precipitation at these stations. Minima are located at stations in Georgia and peninsular Florida, where precipitation on HWDs accounted for < 15% of total precipitation. This indicates that precipitation on HWDs does in fact exhibit its own geographic variations across the 40 stations examined in this study, and that Figure 3.1A does not merely reflect the general precipitation climatology of the SEUS.

The percentage of precipitation that falls on HWDs varies seasonally across the study area (Figure 3.2). During spring, the stations in the western half of the study area experience the greatest percentages of precipitation on HWDs, which account for ≥ 25% of the seasonal precipitation totals at these stations. Stations in the eastern half of the study area received less precipitation on HWDs during spring. During summer and fall, a much higher proportion

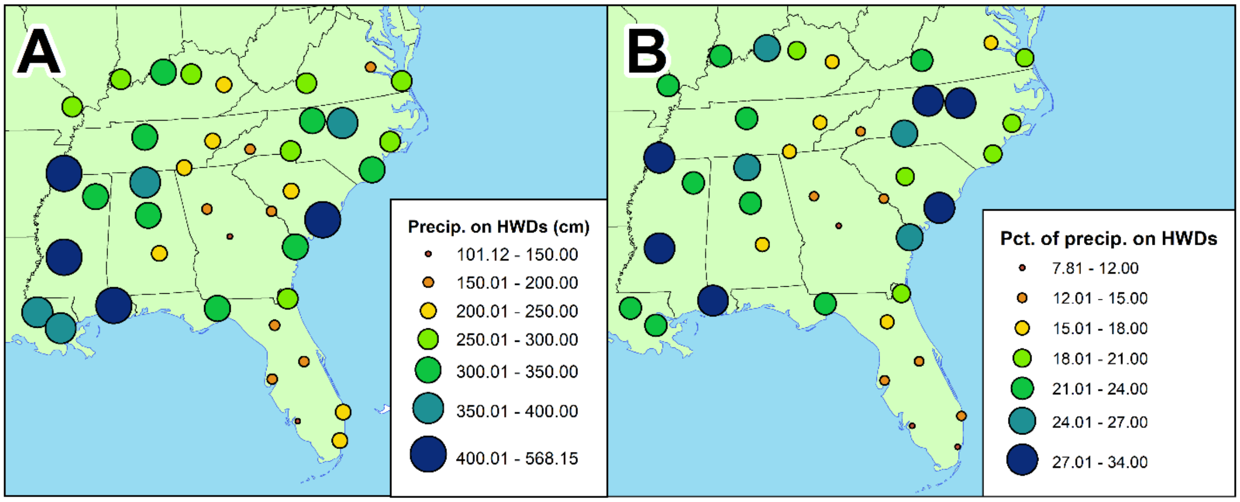

Figure 3.1. Precipitation on HWDs expressed in cm, and percent of total precipitation.

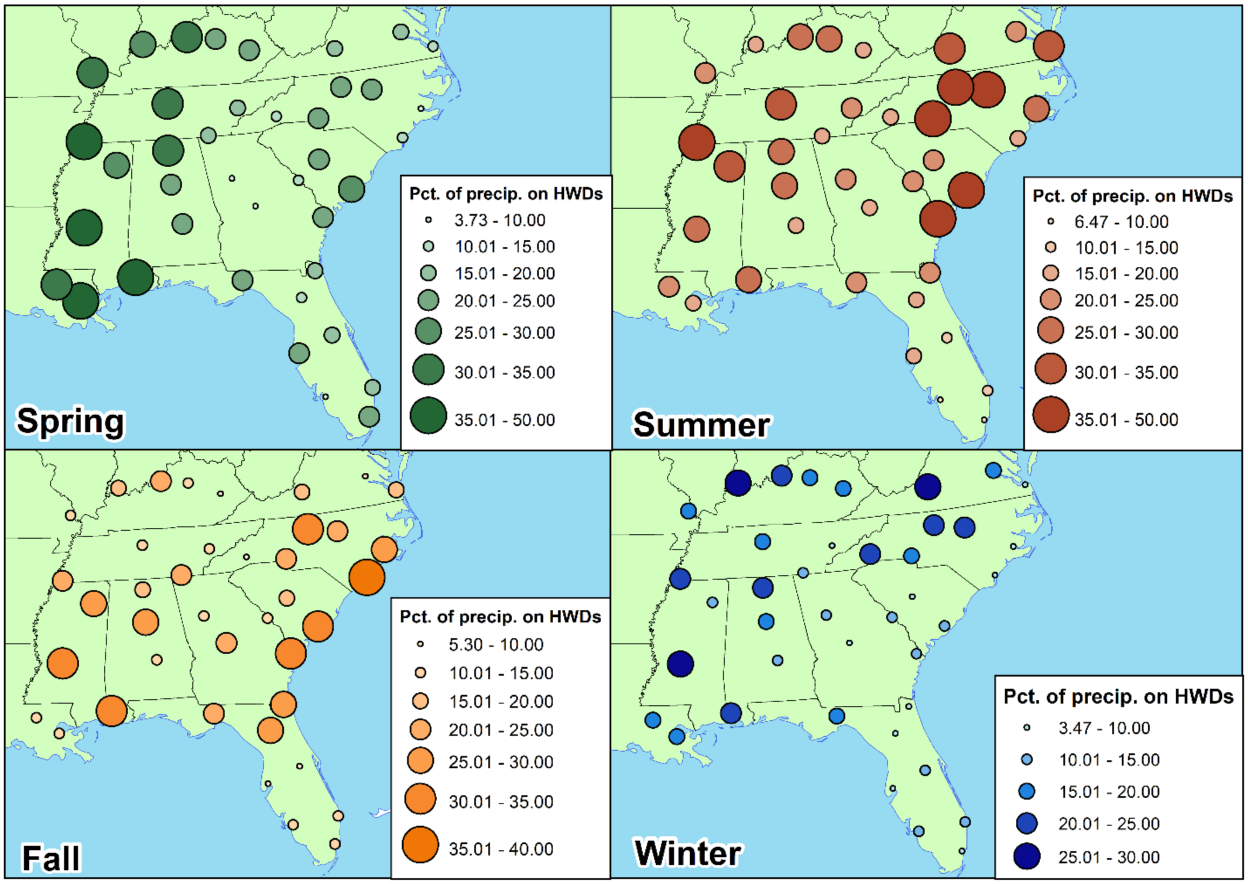

Figure 3.2. Percentage of total precipitation which occurs on HWDs, by season.

(>25%) of precipitation occurs on HWDs east of the Appalachians, while stations in the Ohio Valley and peninsular Florida receive low proportions of precipitation on HWDs.Most stations received a relatively low percentage of precipitation on HWDs during winter compared to other seasons. The highest percentage during winter were at stations in the Ohio and Mississippi Valleys, as well as stations in interior North Carolina and Virginia.

The percentage of precipitation that occurred on HWDs, varied by SSC type (Figure 3.3). The three dry SSC types (Dry Polar, Dry Moderate, Dry Tropical) are not shown because few HWDs occurred during these SSC types. On Moist Polar (MP) days, the stations that received the highest proportion of precipitation on HWDs were in the northern part of the study area and in the lee of the Appalachians. These percentages on MP days decreased substantially further to the south, with stations in peninsular Florida not experiencing any MP HWDs. The percentage of precipitation on Moist Moderate (MM) and Moist Tropical (MT) HWDs varied substantially throughout the study region, with stations in the lower Mississippi Valley, Gulf Coast, and Carolinas exhibiting the highest percentages. These geographic patterns broadly match those in Figure 3.1. One important difference between the MM and MT maps in Figure 3.3 is that the stations in the eastern half of the study area received greater percentages of precipitation on MT HWDs relative to MM HWDs. This is particularly apparent in Greensboro and Raleigh, NC; Charleston, SC; Roanoke, VA; and Savannah, GA. These same stations experience a greater proportion of precipitation on HWDs in summer and fall than during spring (Figure 3.2).

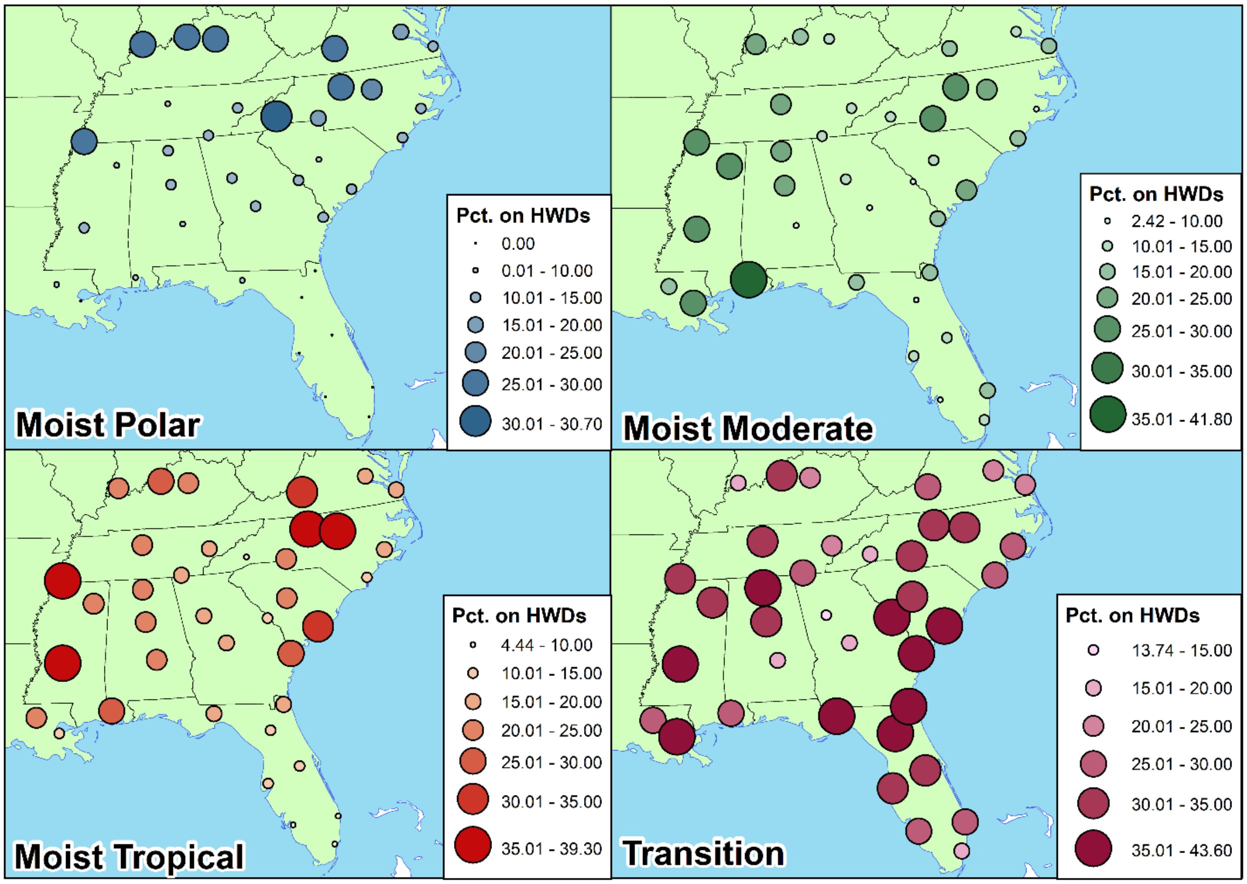

Figure 3.3. Percentage of precipitation which occurs on HWDs, by SSC type.

HWDs accounted for the largest proportion of precipitation on Transition days, relative to the other SSC types, for most of the study area. Of the 38 stations with SSC data, 28 received ≥ 25 percent of Transition precipitation on HWDs, and 20 received > 30% of Transition precipitation on HWDs. This shows the importance of Transition SSC types in the hazardous weather climatology of the region. These patterns are distinct from the overall SSC patterns at these stations (appendix Table A2, Figure A2).

3.5 Discussion

Measuring and identifying patterns in precipitation on HWDs provides insight on the role of hydrometeorologically hazardous events in the climatology of the SEUS. For example, the two geographic maxima in precipitation on HWDs in Figure 3.1—the lower Mississippi Valley and the Carolinas—have separate characteristics. The stations in the lower Mississippi Valley receive higher total amounts of precipitation on HWDs (Figure 3.1), and higher seasonal proportion during spring (Figure 3.2) and synoptic proportions on MM SSC days (Figure 3.3) relative to most other stations in the study region. Stations in the Carolinas receive only moderate precipitation totals on HWDs, but this precipitation comprises a relatively large proportion of total precipitation (Figure 3.1). Precipitation on HWDs at these stations is also relatively common during summer (Figure 3.2) and on MT days (Figure 3.3), relative to other stations. A likely explanation for these differences is the meteorological mechanisms responsible for HWDs: strong mid-latitude cyclones producing precipitation and hazardous weather during spring in the Mississippi Valley, while airmass thunderstorms and tropical cyclones produce precipitation and hazardous weather east of the Appalachians during summer.

The findings on precipitation on HWDs by SSC type (Figure 3.3) connect hydrometeorologically hazardous events, which usually occur on the mesoscale, to broader synoptic weather types. Synoptic weather-type frequency trends are a common avenue of research, especially for multidecadal time scales. For example, Senkbeil et al. (2017) showed that warm season (May–September) MT (MM) days became more (less) common and across the Southeast between 1950–015. Since the mid-Atlantic region receives high proportions of precipitation during summer (Figure 3.2) and MT (Figure 3.3) HWDs, this suggests that synoptic weather types favorable for hydrometeorologically hazardous weather events in this region have increased in frequency over the last several decades. Furthermore, intense precipitation events in the Southeast have been increasingly occurred on MT days (Skeeter *et al.* 2019). Additional research (e.g., Ferreira et al. 2018) may be able to determine if this trend will continue.

High percentages of precipitation on MP days occurred on HWDs for stations in western North Carolina and Virginia. This is likely caused by hazardous winter weather during instances of Appalachian cold air damming, which has been identified using MP SSC types in previous research (Ellis, Marston, *et al.* 2018). While long terms trends in cold air damming are insignificant, El Niño conditions are favorable for winter season cold air damming (Ellis, Marston, *et al.* 2018), and perhaps precipitation on HWDs in this region of the study area as well.

Nearly all stations in the study area experienced a high proportion of precipitation on HWDs during Transition SSC types (Figure 3.3). While the association between hazardous weather and changing airmasses is well established, this finding confirms the importance of monitoring trends in Transition SSC days over long time periods as these trends relate to the future of hazardous weather in the region. Observed decreases in winter Transition type frequency (Hondula and Davis 2011a) in the SEUS may partially decrease the amount of precipitation on HWDs, opposing the effect of increased summer season MT days.

Data missingness is another factor to consider when interpreting the results. Precipitation data were complete across the entire study period for all but five of the stations included in Table 3.1. Stations at Fort Myers, FL; Evansville, IN; Cape Girardeau, MO; Greenville, NC; and West Palm Beach, FL were missing 14 daily precipitation readings or fewer from a total of 3652 days in the study period, for a missingness rate of 0.38% or lower. Of these missing data points, three days at Cape Girardeau, MO and two at Evansville, IN were HWDs, compared to a total of 109 HWDs at both stations, for a missingness rate of 2.75% and 1.83% for HWD precipitation at those two stations respectively, and 0.0% at all other stations. Thus, precipitation totals on HWDs may be slightly undercounted at these two stations, while the proportion of total precipitation that falls on HWDs may be slightly overcounted at Fort Myers, FL, Greenville, NC, and West Palm Beach, FL.

3.6 Conclusions

Using an NWS warning-based approach, we calculate precipitation totals on hydrometeorologically HWDs in the SEUS and identify synoptic weather types on these HWDs. Stations along the Gulf Coast, lower Mississippi Valley, and Carolinas receive the most precipitation on HWDs, in both absolute amounts and proportion of total annual precipitation. Seasonally, stations in the Mississippi Valley and mid-South receive high proportions of precipitation on HWDs during spring, while stations east of the Appalachians and on the Atlantic Coast receive high proportions of precipitation on HWDs during summer and fall. Synoptically, precipitation on Moist Moderate HWDs is most common at stations in the Mississippi Valley and mid-South, while precipitation on Moist Tropical HWDs is relatively common in the Carolinas and Virginia.

There are several important takeaways from this study. The first is that several distinct hazardous weather regimes exist in the SEUS—the Gulf Coast, mid-South, mid-Atlantic, Florida, and southern Appalachia each have unique characteristics when examining HWDs seasonally and synoptically. This is an important consideration for research on past and future hazardous weather trends in the SEUS; a given climatic trend will likely have different implications for peninsular Florida, for example, than it will for the mid-South or the Carolinas. Using the SSC system to define synoptic weather types, a large proportion of precipitation falls on Transition HWDs across much of the SEUS, as well as on Moist Polar HWDs in the lee of the Appalachians, Moist Moderate HWDs in the lower Mississippi Valley, and Moist Tropical days in the mid-Atlantic and Mississippi Valley. Determining the future trends in these weather types, particularly relative to Dry days on which hazardous weather is rare, may shed light on trends in hazardous weather in a changing climate.

Chapter 4

Intended Response to Tornado Watches among Tennessee Residents

This study is currently in preparation for submission to a peer-reviewed journal. I will be the lead author, but Kelsey Ellis, Lisa Reyes Mason, and Jen First contributed to this study in survey administration and analysis, study design, and manuscript editing.

4.1 Abstract

Tornado watches are alerts issued by the National Weather Service when the atmosphere is favorable for tornado formation over a span of hours, and an individual's response to a tornado watch may affect their ability to seek adequate shelter if a tornado strikes. Here, I use survey data of Tennessee residents to determine common patterns in their intended response to two hypothetical tornado watch scenarios: one during the day, and the other at night. I use a clustering procedure to identify these patterns, and then logistic regressions to determine sociodemographic and cognitive characteristics associated with these common response patterns. The three common patterns for a daytime watch were to do nothing; to seek information using technology; or to seek shelter and pray for safety. The two common patterns for a nighttime watch were to do nothing and continue on as before, or to react actively by seeking further information and shelter and contacting friends and family. Logistic regressions determined that younger participants, those with prior tornado experience, and those who correctly understood a tornado watch were less likely to seek shelter and pray for safety during the daytime, while older participants and those without strong self-efficacy beliefs were less likely to use technology for further information. For the nighttime scenario, participants living in East Tennessee and those who believed that bodies of water provide protection from tornadoes were more likely to respond actively, while those living in single- or multi-family homes were less likely to respond actively. When considering income, wealthier participants were also less likely to respond actively. The results from this study show the importance of age and income in intended tornado alert

response, as do psychological beliefs, understanding of tornado alerts, and past experience with tornadoes.

4.2 Background

4.2.1 Public response to tornado alerts

As meteorological ingredients conducive to severe weather formation are forecasted and realized, several products are issued by various bodies within the National Oceanic and Atmospheric Administration (Brotzge and Donner 2013). A *tornado watch* is issued by the Storm Prediction Center several hours before convective initiation is expected. This indicates that conditions are favorable for severe weather formation, including tornadoes. A *tornado warning* is issued by meteorologists at the local National Weather Service (NWS) office when a tornado has been detected by radar or observed by storm spotters. The main differences between a watch and a warning are timing—watches are valid for several hours, while warnings are valid for an hour or less—and, perhaps most importantly, urgency; tornado watches are usually issued hours before expected tornado formation, while tornado warnings are issued within minutes of formation. As such, the recommended action for a tornado warning—sheltering in an interior location away from windows—would be impractical during a tornado watch. Instead, during a watch the recommended actions are to review one's safety plan and room and to check for supplies (NOAA 2021d).

Of these two types of tornado alerts, a much greater proportion of research has been devoted to tornado warnings, since a tornado warning represents an imminent threat during which protective action must be undertaken to maintain one's safety. Hazards research has found that individuals tend to undertake a series of actions that may include warning receipt and confirmation, risk personalization, and sheltering (Mileti and Sorensen 1990, Brotzge and

Donner 2013). There are many modes of tornado warning receipt, including television (Brown *et al.* 2002, Hammer and Schmidlin 2002, Nunley and Sherman-Morris 2020), internet (Nunley and Sherman-Morris 2020), tornado sirens (Liu *et al.* 1996, Comstock and Mallonee 2005), and cell phone alerts (Sherman-Morris 2010, Casteel and Downing 2013, Jauernic and Van Den Broeke 2016). Having multiple ways of receiving tornado warnings may help members of the public stay aware during a tornado threat (Ellis, Reyes Mason, *et al.* 2020).

Actions undertaken after warning receipt vary widely. Individuals may shelter in place, move to a safer location for shelter, or do nothing. Factors such as having graduated high school (Balluz *et al.* 2000) and being female (Sherman-Morris 2010, Silver and Andrey 2013) make an individual more likely to seek shelter. Additionally, several cognitive factors have been associated with shelter-seeking actions, such as prior experience with a tornado (Senkbeil *et al.* 2012, Silver and Andrey 2013, Walters *et al.* 2019), perceptions of tornado vulnerability and warning accuracy (Blanchard-Boehm and Cook 2004, Walters *et al.* 2019), and fatalism (Schmidlin *et al.* 2009, Senkbeil *et al.* 2012, Walters *et al.* 2019). These are important findings because tornado fatality rates are substantially lower for people who do take shelter than for those who do not (Hammer and Schmidlin 2002), particularly in violent tornadoes (Paul and Stimers 2012).

A few studies have involved tornado watches, most of which examined how well the public differentiates between watches and warnings (Liu *et al.* 1996, Balluz *et al.* 2000, Schultz *et al.* 2010, Sherman-Morris 2010, Silver 2015). The rate of correct differentiation between the two alerts varies by study, but tends to be well over 50 percent, and even as high as 90 percent (Schultz *et al.* 2010). However, while this rate of correct differentiation is relatively high, the tornado watch product in its current form may not be well understood by the general public because of its rigidity in communicating expected tornado severity, risk levels, and recommended safety decisions (Mason and Senkbeil 2015). One example of a tornado watch currently used for situations of elevated risk is called a *Particularly Dangerous Situation* (PDS) tornado watch. PDS tornado watches are rare, but have been found to influence decision-making by members of the public (Gutter *et al.* 2018). Survey participants have indicated that preparation and monitoring were common intended actions when provided with four to eight hours of advanced notice for a possible tornado (Krocak *et al.* 2019). Beyond these findings, little research exists on public action during tornado watches, which remains an important and understudied avenue of inquiry and the subject of this study. Findings from this study may shed light on what actions are undertaken by the general public upon learning of a tornado watch, which may in turn reveal their perceptions and understanding of these alerts. Additionally, precautions undertaken hours before a tornado threatens may affect one's ability to find shelter should a tornado warning be issued later.

4.2.2 Study Area

The Southeast is an important setting for research on societal aspects of the tornado hazard because of the region's high vulnerability to devastating tornadoes. The lower Mississippi and Tennessee River valley regions experience the highest number of killer tornadoes in the nation, despite the climatological tornado maximum existing in the southern Great Plains (Ashley 2007, Fricker *et al.* 2017). The reasons for this high fatality rate in the Southeast are numerous and complex. One of these reasons is that mobile homes, a dangerous place to be during a tornado (Sutter and Simmons 2010) because of their structural characteristics and distance from adequate shelters (Schmidlin *et al.* 2009, Strader *et al.* 2019), comprise a substantial portion of the housing stock in the Southeast (Strader and Ashley 2018). Residents also commonly overestimate their safety in mobile homes (Ash 2017).

The timing of tornadoes is another contributor to fatality rates in the Southeast. Nocturnal tornadoes (Ashley *et al.* 2008b) and the meteorological conditions favorable for their formation (Davies and Fischer 2009, Kis and Straka 2010) are more common in the Southeast than in other tornado-prone regions of the country. Tornadoes occurring between the months of November and February, when day lengths are short, have become more common since the mid-20th century (Childs *et al.* 2018), as have overall tornado reports in the Southeast (Gensini and Brooks 2018) where nocturnal tornadoes are common. This trend is expected to continue (Gensini and Mote 2015). Nocturnal tornadoes are dangerous because members of the public report being less likely to receive tornado warning messages at night (Mason *et al.* 2018), and fatality rates during nocturnal tornadoes are markedly higher than daytime tornadoes (Simmons and Sutter 2005).

4.2.3 Study Goals

In this study, I aim to identify intended actions among members of the public when faced with a tornado watch using survey responses of Tennessee residents. Study results add to the current state of knowledge on public actions undertaken before tornadoes occur that may affect one's likelihood of warning receipt and ultimate survival. While this study is similar to studies on severe weather preparation by Krocak et al. (2019) and tornado warning response by Walters et al. (2019), it is unique in its focus on tornado watch response in the Southeast and its aim to draw connections between sociodemographic and cognitive factors and intended watch response. Study findings allow for easy comparison to established knowledge of public response to tornado warnings. I have two main research questions:

- What patterns of intended behaviors after tornado watch issuance are identifiable, and how can they be grouped into classes?
- What cognitive and sociodemographic characteristics are associated with membership in each class?

4.3 Data and Methods

For this study, I used data obtained via a survey of 1804 people living in twelve counties of Tennessee (Figure 4.1). These counties contain large cities such as Nashville, Memphis, and Knoxville, as well as surrounding suburban, exurban, and rural areas. The survey was approved by the University of Tennessee Institutional Review Board and conducted in the year 2016 over telephone calls to randomly selected phone numbers. Data obtained from this survey have been used in other studies on tornado hazard understanding and response, including Ellis et al. (2018), Mason et al. (2018), and Ellis et al. (2019), and Walters et al. (2019). Participants who gave verbal informed consent to the survey were asked questions about their own sociodemographic characteristics, as well as those in their household; cognitive factors including beliefs and perceptions about tornado threats; and their intended responses to one of several hypothetical scenarios involving tornadoes. Two of these hypothetical tornadoes pertained to a tornado watch issued on a Saturday: one taking place during the afternoon, with the tornado watch valid until 8 PM, and the other taking place at night, with the tornado watch valid until 5 AM Sunday. After being read the details of this tornado watch scenario, participants were asked which of the following actions they would undertake:

1. Do nothing, continue on as before
2. Turn on the television or radio to find more information

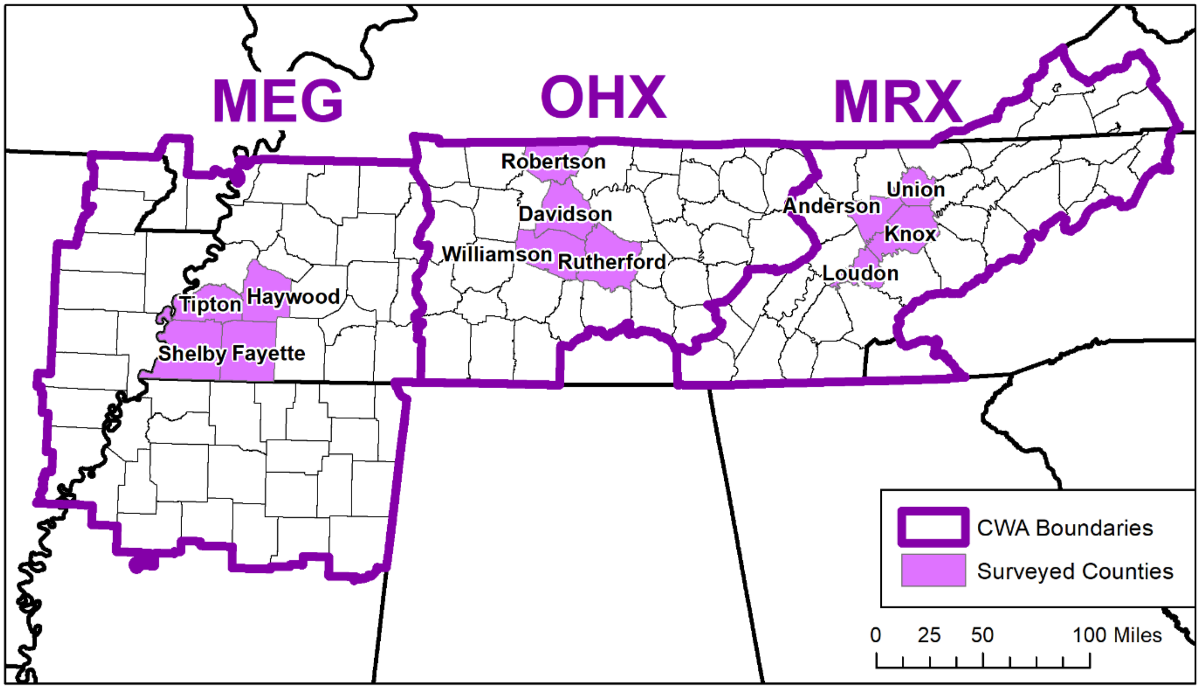

Figure 4.1. Counties in Tennessee included in the survey used for this study.

3. Search the internet to find more information
4. Use an app on a smartphone or tablet to find more information
5. Look or go outside to check the weather yourself
6. Contact friends or family
7. Leave your home
    a. If Yes, where would you go?
8. Pray for safety
9. Something else (specify):

Participants could also answer “I don’t know” or refuse to answer the question. Participants who said they would do nothing could still select other actions they may take. Participants who indicated that they would leave their home upon watch issuance were asked where they would go, and their answers to this question were manually coded into two groups: one of people who indicated to leave their house to find shelter or a safer location, and another for all other answers, *e.g.*, running errands or other locations not chosen specifically for shelter.

Other questions in the survey pertained to participants’ age, gender, income, and education. Other factors described where and with whom the participant lived: one’s home type, the region of Tennessee in which they lived, whether or not they lived with a household member under age 18 or over 65, whether or not they were married or living with a long-term partner, how long they had lived in Tennessee, and if they had access to a basement or storm shelter. Participants were also asked what (if any) prior experience they had with tornadoes and whether they felt that hills, bodies of water, and tall buildings protected nearby areas from tornadoes. Finally, participants were read statements pertaining to one’s belief in self-efficacy: “Except in extreme circumstances, my safety is under my control when a tornado threatens”; luck:

“Surviving a tornado is mostly a matter of luck”; and fatalism: “People die when it is their time and not much can be done about it”; and asked to evaluate the degree to which they agreed with these statements on a Likert scale.

To answer my first research question, I separated the responses by scenario—daytime and nighttime—and used Gower distance to determine the similarity between participants’ answer sets to the nine possible actions above. Separating daytime from nighttime responses allows for examination of whether intended responses differ by time of day, which is an important consideration because of the elevated fatality rate of nocturnal tornadoes. Since individuals tend to undertake a series of actions when responding to hazard alerts rather than only a single action (Mileti and Sorensen 1990, Brotzge and Donner 2013, Walters *et al.* 2019), I categorized similar response sets into clusters to determine common patterns of intended action using partitioning around medoids and silhouette width to optimize the number of clusters. Each cluster thus contained participants with similar intended responses, representing common responses to tornado watch issuance. I examined the proportions of participants in each cluster who indicated that they would undertake each action listed above. For the three (two) clusters in the daytime (nighttime) scenario, I performed pairwise Wilcoxon tests with Bonferroni corrections (χ^2 tests of independence) to determine the clusters in which participants were significantly more or less likely to intend to perform each action.

To answer my second research question, I performed a series of bivariate statistical tests. Each test used cluster membership as the response variable, but had various explanatory variables representing participants’ sociodemographic characteristics; cognitive factors; and experience with and knowledge of tornadoes. I used chi-squared tests of independence to determine significant associations between cluster membership and explanatory variables with three or fewer categories. For explanatory variables with four or more ordinal categories, I used Wilcoxon Mann-Whitney (Kruskal-Wallis) tests to determine significant associations with membership in two (three) categories of intended responses in the night (day) samples. I also used generalized variance inflation factor (<3.0) to ensure that the assumption of no multicollinearity between explanatory variables was met.

The *p*-values from these tests indicate the likelihood that associations between cluster membership and corresponding explanatory variables existed through random chance. I used explanatory variables that produced a *p*-value of 0.30 or lower to build a series of multivariate logistic regressions to determine which explanatory variables were most strongly associated with cluster membership—and therefore intended watch response—when multiple explanatory variables are taken into account. I used several different combinations of explanatory variables in these models, prioritizing inclusion of explanatory variables with low bivariate *p*-values, and used Akaike Information Criterion and residual deviance to select the model containing the optimal combination of explanatory models that best fit the data. I also used generalized variance inflation factor to ensure a lack of problematic multicollinearity.

4.4 Results

A majority of participants identified as female, white, and married or living with a long-term partner without anyone under the age of 18 or over age 65 in the household (Table 4.1). They also tended to live in single- or multi-family households and had a cell phone, but did not have access to a basement or shelter. There were a few significant ($\alpha = 0.05$) differences between the daytime and nighttime participants' sociodemographic and cognitive characteristics (Table 4.1), but the sample populations were mostly similar. Some intended responses differed between

Table 4.1. Sample characteristics for participants in the daytime and nighttime scenarios.

Variable	**Day (mean or percentage)** ***n* = 444**	**Night (mean or percentage)** ***n* = 202**	***p*-value of day/night difference (test)**
Gender: female	64.1	60.2	0.391 (χ^2)
Age (years)	57.1	51.9	<0.01 (Wilcoxon Mann Whitney)
Race:			0.238 (χ^2)
White	79.9	75.4	
Non-white	20.1	24.6	
Income, assessed in 12 intervals of 10k USD and numbered 1–12	5.67	5.22	0.157 (Wilcoxon Mann Whitney)
Education:			
High school diploma or less	26.8	28.5	0.842 (χ^2)
Some college, technical, or associates degree	35.1	33.0	
College degree or more	38.1	38.5	
Married or living with long-term partner	62.2	57.6	0.310 (χ^2)
Someone under age 18 in household	25.1	26.6	0.745 (χ^2)
Someone over age 65 in household	46.2	37.5	0.049 (χ^2)
Years living in Tennessee	40.3	37.7	0.164 (Wilcoxon Mann Whitney)
Had smartphone	67.1	75.2	0.036 (χ^2)
Home type:			
Single- or multi-family home	82.0	77.2	0.192 (χ^2)
Mobile home, apartment, condominium, or other	18.0	22.8	
Access to basement or storm shelter	23.7	24.9	0.821 (χ^2)
Live in rural area	49.0	39.1	0.028 (χ^2)
Region of Tennessee:			
West	35.0	38.1	0.199 (χ^2)
Middle	30.7	34.7	
East	34.3	27.2	

Table 4.1 continued.

Variable	Day (mean or percentage) n = 444	Night (mean or percentage) n = 202	p-value of day/night difference (test)
Prior experience with tornadoes:			
Not nearby	35.0	35.7	0.734 (χ^2)
Near where I live	52.8	54.3	
Hit home or building	12.2	10.1	
Efficacy:			
Strongly agree	20.3	23.4	0.175 (Wilcoxon Mann Whitney)
Agree	46.7	46.8	
Disagree	21.0	23.9	
Strongly disagree	12.1	6.0	
Luck:			
Strongly disagree	21.9	15.6	0.004 (Wilcoxon Mann Whitney)
Disagree	47.6	43.2	
Agree	23.3	29.6	
Strongly agree	7.2	11.6	
Fatalism:			
Strongly disagree	14.3	9.8	0.042 (Wilcoxon Mann Whitney)
Disagree	35.8	34.0	
Agree	34.7	35.1	
Strongly agree	15.2	21.1	
Tornado watch knowledge	82.7	79.0	0.315 (χ^2)
Belief in protection from hills:			
Not at all	15.9	22.9	0.071 (χ^2)
Somewhat	55.3	47.9	
Very much or completely	28.8	29.2	

Table 4.1 continued.

Variable	Day (mean or percentage) n = 444	Night (mean or percentage) n = 202	p-value of day/night difference (test)
Belief in protection from water:			
Not at all	57.8	54.4	0.221 (χ^2)
Somewhat	34.1	33.2	
Very much or completely	8.1	12.4	
Belief in protection from buildings:			
Not at all	67.0	64.7	0.151 (χ^2)
Somewhat	37.2	25.4	
Very much or completely	5.7	10.0	

the two samples (Table 4.2), including the day group being more likely to check the weather outside or leave their home, and the night group being more likely to use an app or smart phone.

I determined the optimal number of clusters for analysis by examining silhouette width. For the daytime scenario participants, silhouette width was maximized with three clusters (Figure 4.2), and for the nighttime scenario participants, silhouette width was maximized with two clusters (Figure 4.3). Thus, I proceeded with bivariate analysis and logistic regressions using three daytime clusters and two nighttime clusters. The intended responses for each cluster are shown below (Tables 4.3 and 4.4).

Each daytime cluster exhibited unique characteristics in terms of intended response to a hypothetical tornado watch (Table 4.3). Cluster 1 was the largest of the three clusters and members were significantly ($\alpha = 0.05$) more likely than other clusters to intend to seek shelter in their home and pray for safety upon watch issuance. Participants in Cluster 2 were most likely to indicate that they would do nothing and continue on as before after hearing of a watch. They were least likely to indicate that they would seek shelter in their home, contact friends and family, pray for safety, or turn on the television or radio for more information. Cluster 3 was the smallest cluster, but every member of this cluster indicated that they would search the internet and use an app on a smartphone or tablet for more information. Thus, when examining the intended responses of daytime survey participants, three common patterns are apparent: one group reacts strongly, seeking shelter and praying for safety (Cluster 1); one group seeks more information through the internet, smartphones, or tablets (Cluster 3); and one group is comparatively unreactive (Cluster 2). However, it is important to note that some intended actions—such as turning on the television or radio, checking the weather oneself, or praying for

Table 4.2. Intended responses to the given tornado watch scenario.

Intended Response	Percentage in Daytime Group	Percentage in Nighttime Group	χ^2 *p*-value
Do nothing, continue on as before	46.2	41.6	0.317
Turn on the television or radio to find out more information	93.0	91.6	0.630
Search the internet to find out more information	31.3	36.1	0.262
Use an app on a smartphone or tablet to find out more information	47.3	60.4	0.003
Look or go outside to check the weather yourself	76.1	65.3	0.006
Contact friends or family	76.8	72.8	0.315
Seek shelter in your home	57.4	59.4	0.700
Leave your home:			
No	82.7	87.6	0.016
Somewhere specifically for shelter	13.1	5.9	
Anywhere else	4.3	6.4	
Pray for safety	82.0	79.2	0.467

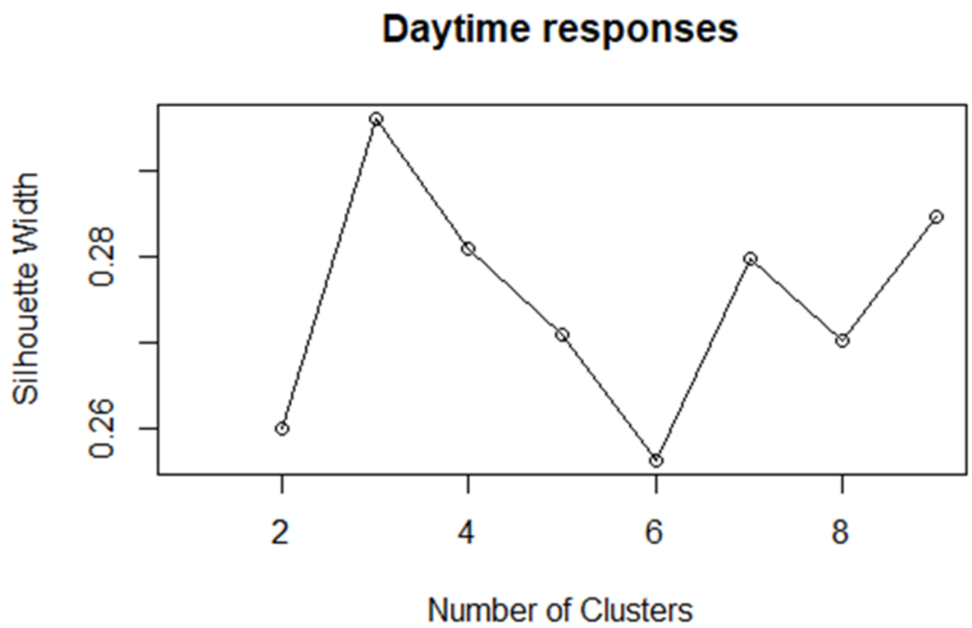

Figure 4.2. Silhouette width by number of clusters for the daytime sample.

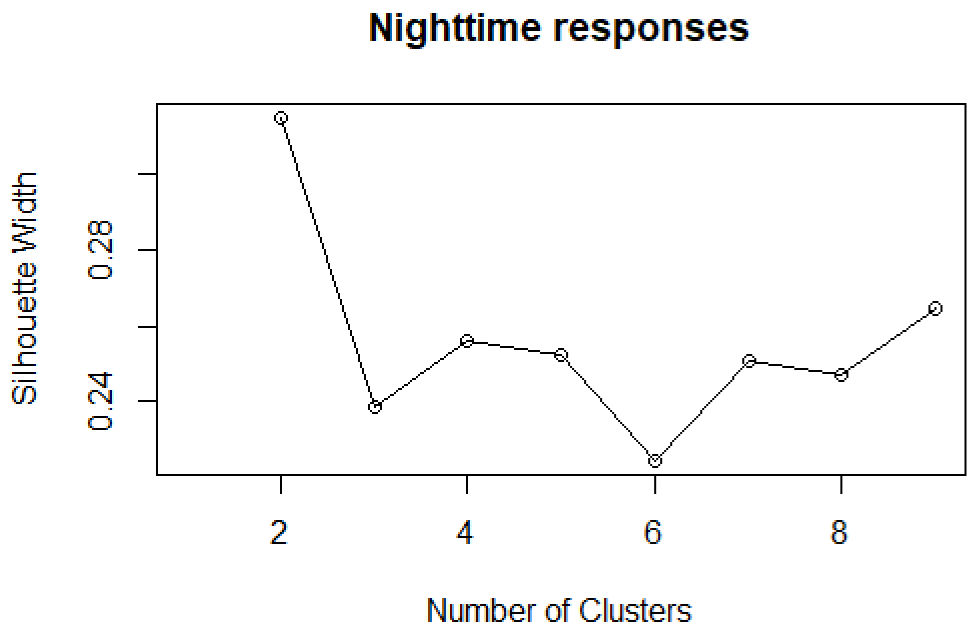

Figure 4.3. As in Figure 4.2, but for the nighttime sample.

Table 4.3. Intended responses by cluster for the daytime scenario. Pairwise Wilcoxon significance (α = 0.05) is indicated with plus signs (+) and minus signs (-): a cluster with a significantly higher rate than one other cluster is denoted with a single plus sign, significantly higher than both clusters denoted with two plus signs, etc.

Intended Response	**Cluster 1 (*n* = 214)**	**Cluster 2 (*n* = 131)**	**Cluster 3 (*n* = 99)**
Do nothing, continue on as before	29.4 –	88.5 + +	26.3 –
Turn on the television or radio to find out more information	97.2 +	84.7 – –	94.9 +
Search the internet to find out more information	11.7 –	11.5 –	100.0 + +
Use an app on a smartphone or tablet to find out more information	29.4 –	36.6 –	100.0 + +
Look or go outside to check the weather yourself	78.5	71.8	76.8
Contact friends or family	95.3 +	36.6 – –	89.9 +
Seek shelter in your home	85.5 + +	11.5 – –	57.6 + –
Leave your home: **No** **Somewhere specifically for shelter** **Anywhere else**	 86.5 5.1 8.4	 76.3 1.5 22.1	 82.8 6.1 11.1
Pray for safety	92.5 + +	65.6 – –	80.8 + –

Table 4.4. As in Table 4.3, but for the nighttime scenario.

Intended Response	Cluster 1 (*n* = 139)	Cluster 2 (*n* = 63)
Do nothing, continue on as before	0.230 -	0.825 +
Turn on the television or radio to find out more information	0.957 +	0.825 -
Search the internet to find out more information	0.432 +	0.206 -
Use an app on a smartphone or tablet to find out more information	0.727 +	0.333 -
Look or go outside to check the weather yourself	0.741 +	0.460 -
Contact friends or family	0.914 +	0.318 -
Seek shelter in your home	0.770 +	0.206 -
Leave your home: **No** **Somewhere specifically for shelter** **Anywhere else**	 87.8 8.6 3.6	 87.3 0.0 12.7
Pray for safety	0.842 +	0.683 -

safety—were common across all three clusters, with over half of participants in each cluster indicating that they would do so.

The two nighttime clusters also exhibited significant ($\alpha = 0.05$) differences in intended responses (Table 4.4). A significantly higher proportion of survey participants in Cluster 1 indicated that they would undertake nearly all of the actions provided in the survey. A higher proportion of participants in Cluster 2 were likely to do nothing and continue on. The two common patterns for participants in the nighttime scenario were to react actively (Cluster 1) or to be relatively unreactive (Cluster 2). As with the daytime scenario, over half of participants in each cluster indicated that they would turn on the television or radio for more information and pray for safety upon learning of the tornado watch.

Bivariate tests indicated that cluster membership was not independent of some sociodemographic characteristics and cognitive factors included in the survey. Significant ($\alpha = 0.05$) differences between daytime scenario clusters exist for having a household member over age 65, the number of years the participant has lived in Tennessee, proper understanding of a tornado watch, beliefs in protection from buildings, and cognitive factors regarding efficacy and fatalism (Table 4.5). These variables were tested for inclusion in a multivariate logistic regression to predict cluster membership. Other variables returned relatively low p-values, though not significant at $\alpha = 0.05$, that were also tested for this regression.

The two clusters of participants in the nighttime scenario also exhibited differences in some sociodemographic and cognitive variables (Table 4.6). Home type and region of Tennessee were significant at the $\alpha = 0.05$ level, with higher proportions of participants in Cluster 2 living in single- or multi-family homes and in West or Middle Tennessee. Income and beliefs in efficacy and protection from water were significant at $\alpha = 0.10$. As with the daytime clusters,

Table 4.5. Characteristics by cluster and bivariate significance for the daytime scenario.

Variable	Cluster 1 (mean or percentage)	Cluster 2 (mean or percentage)	Cluster 3 (mean or percentage)	*p*-value (test)
Gender: female	63.1	68.0	61.2	0.527 (χ^2)
Age (years)	58.6	56.4	57.3	0.434 (Kruskal Wallis)
Race:				0.986 (χ^2)
White	79.6	80.0	80.4	
Non-white	20.4	20.0	19.6	
Income, assessed in 12 intervals of 10k USD and numbered 1–12	5.5	5.6	6.1	0.366 (Kruskal Wallis)
Education:				
High school diploma or less	29.1	23.1	26.5	0.453 (χ^2)
Some college, technical, or associates degree	31.9	41.5	33.7	
College degree or more	39.0	35.4	39.8	
Married or living with long-term partner	59.9	61.5	68.0	0.386 (χ^2)
Someone under age 18 in household	20.6	26.0	33.7	0.044 (χ^2)
Someone over age 65 in household	51.4	51.9	27.3	< 0.001 (χ^2)
Years living in Tennessee	45.3	38.2	32.5	< 0.001 (Kruskal Wallis)
Had smartphone	67.0	69.2	66.0	0.859 (χ^2)

Table 4.5 continued.

Variable	**Cluster 1 (mean or percentage)**	**Cluster 2 (mean or percentage)**	**Cluster 3 (mean or percentage)**	***p*-value (test)**
Home type:				
Single- or multi-family home	80.0	88.5	77.6	0.062 (χ^2)
Mobile home, apartment, condominium, or other	20.0	11.5	22.4	
Access to basement or storm shelter	25.9	27.3	34.0	0.339 (χ^2)
Live in rural area	47.4	53.5	46.3	0.464 (χ^2)
Region of Tennessee:				
West	33.6	37.4	34.7	0.102 (χ^2)
Middle	27.1	29.8	39.8	
East	39.3	32.8	25.5	
Prior experience with tornadoes:				
Not nearby	38.8	32.8	29.6	0.268
Near where I live	51.4	55.0	53.1	
Hit home or building	9.8	12.2	17.3	
Efficacy:				
Strongly agree	18.5	14.5	32.0	0.004 (Kruskal Wallis)
Agree	51.2	43.5	41.2	
Disagree	19.0	26.7	17.5	
Strongly disagree	11.4	15.3	9.3	

Table 4.5 continued.

Variable	**Cluster 1 (mean or percentage)**	**Cluster 2 (mean or percentage)**	**Cluster 3 (mean or percentage)**	***p*-value (test)**
Luck:				
Strongly disagree	22.0	19.2	25.3	0.334 (Kruskal Wallis)
Disagree	45.3	50.0	49.5	
Agree	22.4	26.2	21.2	
Strongly agree	10.3	4.6	4.0	
Fatalism:				
Strongly disagree	13.1	17.8	12.2	0.021 (Kruskal Wallis)
Disagree	31.3	43.4	35.7	
Agree	37.9	26.4	38.8	
Strongly agree	17.8	12.4	13.3	
Tornado watch knowledge	75.8	90.0	87.8	0.001 (χ^2)
Belief in protection from hills:				
Not at all	19.9	12.2	12.2	0.211 (χ^2)
Somewhat	51.7	61.1	56.1	
Very much or completely	28.4	26.8	31.6	
Belief in protection from water:				
Not at all	59.6	57.4	54.6	0.371 (χ^2)
Somewhat	30.3	37.2	38.1	
Very much or completely	10.1	5.5	7.2	

Table 4.5 continued.

Variable	Cluster 1 (mean or percentage)	Cluster 2 (mean or percentage)	Cluster 3 (mean or percentage)	***p*-value (test)**
Belief in protection from buildings:				
Not at all	73.7	64.3	56.6	0.048 (χ^2)
Somewhat	21.5	29.5	36.4	
Very much or completely	4.7	6.3	7.1	

Table 4.6. As in Table 4.5, but for clusters in the nighttime scenario.

Variable	**Cluster 1 (mean or percentage)**	**Cluster 2 (mean or percentage)**	***p*-value (test)**
Gender: female	60.9	58.7	0.895 (χ^2)
Age (years)	51.0	53.9	0.197 (Wilcoxon Mann Whitney)
Race: **White** **Non-white**	 72.1 27.9	 82.5 17.5	 0.156 (χ^2)
Income, assessed in 12 intervals of 10k USD and numbered 1–12	4.85	6.12	0.065 (Kruskal Wallis)
Education: **High school diploma or less** **Some college, technical, or associates degree** **College degree or more**	 32.1 32.1 35.8	 20.6 34.9 44.4	 0.230 (χ^2)
Married or living with long-term partner	57.8	57.1	0.980 (χ^2)
Someone under age 18 in household	25.7	28.6	0.804 (χ^2)
Someone over age 65 in household	36.5	39.7	0.783 (χ^2)
Years living in Tennessee	38.5	36.1	0.440 (Wilcoxon Mann Whitney)
Had smartphone	75.4	77.4	0.892 (χ^2)
Home type: **Single- or multi-family home** **Mobile home, apartment, condominium, or other**	 73.3 26.7	 85.5 14.5	 < 0.001 (χ^2)
Access to basement or storm shelter	32.1	27.4	0.617 (χ^2)

Table 4.6 continued.

Variable	Cluster 1 (mean or percentage)	Cluster 2 (mean or percentage)	*p*-value (test)
Live in rural area	39.4	38.3	0.970 (χ^2)
Region of Tennessee:			
West	36.0	42.9	0.049 (χ^2)
Middle	31.7	41.3	
East	32.4	15.9	
Prior experience with tornadoes:			
Not nearby	36.5	33.9	0.714 (χ^2)
Near where I live	52.6	58.1	
Hit home or building	19.9	8.1	
Efficacy:			
Strongly agree	25.4	19.0	0.057 (Wilcoxon Mann Whitney)
Agree	50.0	39.7	
Disagree	18.1	36.5	
Strongly disagree	6.5	4.8	
Luck:			
Strongly disagree	16.1	14.5	0.983 (Wilcoxon Mann Whitney)
Disagree	42.3	45.2	
Agree	29.9	29.9	
Strongly agree	11.7	11.3	
Fatalism:			
Strongly disagree	10.4	8.3	0.988 (Wilcoxon Mann Whitney)
Disagree	32.1	38.3	
Agree	37.3	30.0	
Strongly agree	20.1	23.3	
Tornado watch knowledge	81.0	74.6	0.396 (χ^2)

Table 4.6 continued.

Variable	Cluster 1 (mean or percentage)	Cluster 2 (mean or percentage)	p-value (test)
Belief in protection from hills:			
Not at all	19.9	28.3	0.423 (χ^2)
Somewhat	48.5	43.3	
Very much or completely	31.6	28.4	
Belief in protection from water:			
Not at all	48.9	66.7	0.054 (χ^2)
Somewhat	36.1	26.7	
Very much or completely	15.0	6.7	
Belief in protection from buildings:			
Not at all	62.3	69.8	0.436 (χ^2)
Somewhat	26.1	23.8	
Very much or completely	11.5	6.3	

variables with low bivariate *p*-values were tested in a series of multivariate logistic regressions to predict cluster membership.

After testing several combinations of explanatory variables with low bivariate *p*-values (Table 4.5) in a logistic regression, I selected the regression with the best data fit and minimal deviance and multicollinearity to model daytime cluster membership as a function of sociodemographic and cognitive characteristics. I used daytime Cluster 2 (unreactive) as the reference group to examine which characteristics were associated with membership in Clusters 1 and 3.

In the selected regression (Table 4.7), a participant was more likely ($\alpha = 0.05$) to be in Cluster 1 (shelter seeking; praying) if they were older or did not know the meaning of a tornado watch. Participants were less likely to be in Cluster 1 if they believed that cities are "somewhat" protected from tornadoes by buildings ($\alpha = 0.05$) or if they reported experience with a tornado hitting their home or building ($\alpha = 0.10$). A participant was more likely to be in Cluster 3 (information seeking on internet, smartphones, or tablets) if they responded to the statement, "People die when it is their time and not much can be done about it" with "Agree" rather than "Strongly disagree" ($\alpha = 0.10$). At the $\alpha = 0.05$ level, participants were less likely to be in Cluster 3 if they had a household member over age 65 or responded to the efficacy statement ("Except in extreme circumstances, my safety is under my control when a tornado threatens") with a response other than "Strongly agree". At the $\alpha = 0.10$ level, older participants and those who live in a single- or multi-family home were less likely to be classified in Cluster 3.

I repeated the process to predict nighttime cluster membership, once again testing different combinations of explanatory variables with relatively low *p*-values in Table 4.6 with the

Table 4.7. Results of a multinomial logistic regression to predict cluster membership for the daytime scenario. Bolded values indicate significance at the α = 0.05 level, and italicized values indicate significance at the α = 0.10 level.

Explanatory variable	**Cluster 1 coefficient**	**Cluster 1 standard error**	**Cluster 1 *p*-value**	**Cluster 3 coefficient**	**Cluster 3 standard error**	**Cluster 3 *p*-value**
Intercept	**1.650**	**0.700**	**0.018**	1.327	0.700	0.103
Age (years)	**0.017**	**0.006**	**0.005**	*-0.014*	*0.007*	*0.064*
Household resident(s) over age 65	-0.327	0.266	0.220	**-0.828**	**0.323**	**0.010**
Correct knowledge of a tornado watch	**-1.268**	**0.384**	**<0.001**	-0.139	0.475	0.769
Efficacy, "Strongly agree" reference:						
"Agree"	0.319	0.357	0.372	**-0.772**	**0.388**	**0.047**
"Disagree"	-0.246	0.400	0.538	**-1.019**	**0.448**	**0.023**
"Strongly disagree"	-0.316	0.446	0.480	**-1.185**	**0.528**	**0.025**
Fatalism, "Strongly disagree" reference:						
"Disagree"	-0.125	0.377	0.740	0.266	0.454	0.558
"Agree"	0.560	0.394	0.156	*0.799*	*0.473*	*0.091*
"Strongly agree"	0.369	0.462	0.425	0.274	0.587	0.640
Belief in protection by buildings, "none" reference:						
"Somewhat"	**-0.698**	**0.289**	**0.016**	0.364	0.319	0.254
"Very much/completely"	-0.729	0.572	0.202	0.400	0.609	0.511

Table 4.7 continued.

Explanatory variable	**Cluster 1 coefficient**	**Cluster 1 standard error**	**Cluster 1 *p*-value**	**Cluster 3 coefficient**	**Cluster 3 standard error**	**Cluster 3 *p*-value**
Household resident(s) under age 18	-0.364	0.307	0.236	-0.086	0.343	0.802
Single- or multi-family home	-0.486	0.344	0.158	*-0.704*	*0.390*	*0.071*
Prior experience with a tornado, "not nearby" reference:						
Nearby	-0.237	0.269	0.379	0.047	0.328	0.885
Hit home or building	*-0.828*	*0.427*	*0.053*	0.398	0.465	0.382

goal of optimizing model fit, minimizing deviance, and avoiding multicollinearity in explanatory variables. One of the explanatory variables that was strongly correlated with cluster membership in Table 4.6 was income. However, of the 202 nighttime survey participants who were clustered, 33 (16.3 percent) did not report their income. This was a much higher rate of missingness than other variables. To account for this, I created two regressions: one including income as an explanatory variable, and the other without income, but with a larger sample size of participants. I used nighttime Cluster 2 (nonreactive) as the reference category for both regressions.

Without including income as an explanatory variable, survey participants living in East Tennessee and those who believe that water bodies offer “very much” or “complete” protection from tornadoes to nearby areas are significantly ($\alpha = 0.05$) more likely to be classified in Cluster 1 and react relatively strongly to a tornado watch (Table 4.8). Those who believe that locations near water bodies are “somewhat” protected from tornadoes are also more likely to be classified in Cluster 1, but this is only significant at the $\alpha = 0.10$ level. Participants living in single- or multi-family homes were also significantly less likely to be classified in Cluster 1 ($\alpha = 0.10$).

Inclusion of income as an explanatory variable decreased the sample size for the regression, and affected its coefficients and their corresponding significance (Table 4.9). None of the explanatory variables were significant at $\alpha = 0.05$, but three were significant at $\alpha = 0.10$. As in the nighttime regression that did not include an income variable, participants who lived in East Tennessee or those who believed that locations are “somewhat” protected by nearby water bodies were more likely to be classified in Cluster 1. Income was also a significant variable in this regression, with increasing income negatively correlated with Cluster 1 membership.

Table 4.8. Results of a binomial logistic regression to predict cluster membership in the nighttime scenario, with income not included. Bolded values indicate significance at the α = 0.05 level, and italicized values indicate significance at the α = 0.10 level.

Explanatory Variable	Cluster 1 Coefficient	Cluster 1 Standard Error	Cluster 1 *p*-value
Intercept	0.878	0.569	0.123
Single- or multi-family home	*-0.800*	*0.446*	*0.073*
Region of Tennessee, West reference:			
Middle	-0.016	0.383	0.966
East	**0.926**	**0.462**	**0.045**
Belief in protection by water, "none" reference:			
"Somewhat"	*0.619*	*0.373*	*0.098*
"Very much/completely"	**1.234**	**0.611**	**0.044**
Efficacy, "Strongly agree" reference:			
"Agree"	0.005	0.437	0.991
"Disagree"	-0.682	0.483	0.158
"Strongly disagree"	0.495	0.777	0.524
Race: nonwhite	0.630	0.429	0.142

Table 4.9. As in Table 4.8, but with the inclusion of income as an explanatory variable.

Explanatory variable	Cluster 1 coefficient	Cluster 1 standard error	Cluster 1 *p*-value
Intercept	**1.513**	**0.648**	**0.020**
Single- or multi-family home	-0.659	0.499	0.187
Region of Tennessee, West reference:			
Middle	0.387	0.440	0.379
East	*0.871*	*0.498*	*0.081*
Belief in protection by water, "none" reference:			
"Somewhat"	*0.804*	*0.419*	*0.055*
"Very much/completely"	0.527	0.654	0.421
Efficacy, "Strongly agree" reference:			
"Agree"	-0.369	0.490	0.452
"Disagree"	-0.769	0.560	0.170
"Strongly disagree"	0.058	0.806	0.943
Race: nonwhite	0.337	0.467	0.470
Income, assessed in 12 intervals of 10k USD and numbered 1–12	*-0.090*	*0.051*	*0.079*

4.5 Discussion

Since nocturnal tornadoes are common across the Southeast and because fatality rates are higher for these nocturnal tornadoes, examining differences between intended responses in the daytime and nighttime scenario may provide important knowledge on how public preparedness for a tornado varies based on time of day. Between the two scenarios, there were three significantly disproportionate differences in intended warning responses (Table 4.2). First, a higher proportion of participants indicated that they would go outside to check the weather themselves for the daytime scenario, likely because nighttime scenario participants may not have felt that this was a helpful option. Nighttime participants were, however, more likely than their counterparts in the daytime scenario to use a smartphone or tablet app to find more information (Table 4.2), which may have been for them an alternative to checking the weather oneself after nightfall. This difference may also be attributable to sociodemographic differences between participants in the two scenarios: nighttime participants were significantly younger and more likely to own a smartphone (Table 4.1) than those in the daytime scenario. Finally, higher proportions of the daytime scenario participants indicated that they would leave the house upon learning of a tornado watch, and although many answers were not specific regarding the purpose of their trips and their intent may have been for regular activities that they tend to perform on Saturday afternoons.

Within the three clusters of daytime scenario respondents, Cluster 1 was likely to take the most extreme action, its defining characteristics being to pray for safety and seek shelter in their homes (Table 4.3). Seeking shelter in one’s home is an action more suitable for tornado warnings than watches, since watches do not indicate that a tornado is imminent or ongoing. Indeed, correct knowledge of a tornado watch definition was negatively correlated with membership in

Cluster 1 (Table 4.7), indicating that those who can correctly identify the implications of an active tornado watch are less likely to undertake actions that are more appropriate for a warning, such as sheltering in place. Those in Cluster 1 relied on the television or radio for more information instead of an app, and were likely to contact friends and family, which is likely related to the older demographic of the group members. A survey participant having experienced a tornado hitting their home or building also made them significantly less likely to be classified in Cluster 1 (Table 4.7), albeit at a lower significance level ($\alpha = 0.10$). Prior research on this pattern has found that individuals who had prior experience with tornadoes were more likely to understand their own county's climatological risk (Ellis, Mason, *et al.* 2018). In terms of response to a tornado warning, rather than a watch, findings are mixed: Paul et al. (2015) found that those with prior experience with tornadoes were less likely to take shelter during the 2011 Joplin, Missouri, tornado, while Silver and Andrey (2013) found that warning compliance was higher for severe weather in Ontario, Canada, that occurred merely three days after a previous tornado. This could indicate that past tornado experience is associated with a better understanding of tornado risk, in terms of both watch response and climatological perceptions, or with a lack of response to future tornado watches or warnings. Future studies could further elucidate the relationship between past tornado experience, risk perception, and alert response.

Cluster 1 membership was negative correlated with the belief that urban areas are "somewhat" protected from tornadoes by tall buildings. This was the only significant relationship with daytime cluster membership and perceptions of tornado protection from land surface features, as explored in Ellis et al. (2019). However, Walters et al. (2019) found that a similar perception of tornado protection by water bodies made survey respondents less likely to use technology to seek information during a daytime tornado warning and less likely to be nonreactive during a nocturnal tornado warning. My finding regarding perceived building protection making one less likely to take actions that include shelter-seeking and prayer does not match thematically with those in Walters et al. (2019), in which similarly misguided perceptions make one less likely to use technology or be non-reactive, nor is there a similar significant effect in this study for those who believe urban areas are “very much” or “completely” protected by buildings (Table 4.7). Thus, the significant coefficient for the “somewhat” protection level may be due to random chance, but additional research on how public misconceptions about tornadoes affect response to alert would be necessary to confirm or refute this.

A notable feature of Cluster 3 in the daytime scenario was that 100 percent of the members indicated they would use the internet and an app (Table 4.3), which is likely related to the relatively young age of this cluster’s members. Participants who had a household member over age 65 or did not have strong beliefs of self-efficacy were less likely to be categorized in this category, relative to Cluster 2, which was known to be generally unreactive. Participants living in a single- or multi-family home were also less likely to be classified in Cluster 3 relative to Cluster 2. This indicates that individuals living in this kind of housing stock are less likely to seek information upon learning of a tornado watch compared to those living in mobile homes or apartments, the latter of which are inadequate for sheltering (Sutter and Simmons 2010). Thus, one’s degree of confidence in sheltering options may influence whether they seek more information about a tornado watch or do nothing and continue on with their prior activities.

Cluster 2 members were more likely to express disbelief in one’s own control during a tornado event, which is not surprising because participants in Cluster 2 were most likely to do nothing upon hearing of a tornado watch and continued on as before. Walters et al. (2019) found a similar pattern in those who had a strong sense of fatalism—"people die when it is their time and not much can be done about it"—and reacted passively to tornado warnings. While it is important to note that I included responses to this same fatalism statement in my analysis and did not find significant results on it, the themes of the findings match: cognitive factors do play a role in determining one's response to tornado alerts.

There were two clusters of intended responses for the nighttime scenario: one cluster (1) that was significantly more likely to intend to take nearly all response actions, and another (2) that continued on as before. The results of the regressions determining cluster membership depended on whether income was included as an explanatory variable. In the regression without income, participants living in East Tennessee and those who believed in protection from water were more likely to be in Cluster 1 and respond more actively to a nighttime tornado watch. This finding may indicate that a lack of familiarity with tornadoes is associated with an active reaction to tornado watches: lakes and rivers in fact do little to inhibit tornadoes, and East Tennessee is climatologically the least active region of the three for tornadoes (Brown *et al.* 2016). Krocak et al. (2019) found that people living in inactive tornado regions expressed uncertainty in what they would do when given four hours of notice before a future severe weather event, a time scale similar to that of a tornado watch. However, other factors in this study such as knowledge of a tornado watch and prior experience with tornadoes did not exhibit significant disproportionality between the two clusters (Table 4.5). Participants living in single- or multi-family houses were less likely be categorized in Cluster 1 (Table 4.8), consistent with the results of the daytime cluster regression in that those who live in this kind of housing stock are less likely to react actively to a tornado watch (Table 4.7).

When income is introduced to the regression as an explanatory variable, the sample size is reduced because missingness was relatively high. Fewer variables yield significant coefficients: income, living in East Tennessee, and belief that bodies of water are “somewhat” protective are the only three. The signs and resulting interpretations of the East Tennessee and water body variables are unchanged from the regression without income: these participants were more likely to be classified in Cluster 1, indicating an active response to a nighttime tornado watch. Income, measured in increments of 10,000 USD, was negatively associated with Cluster 1 membership, indicating that wealthier participants were less likely to react strongly to a nighttime watch.

4.6 Conclusions

In this study, I examined intended responses to issuance of tornado watches among members of the public in Tennessee, USA. I used Gower distance, partitioning around medoids, and silhouette width to identify three common patterns of intended response for a daytime watch, and two patterns of intended response for a nighttime watch. Then, I used logistic regressions to determine sociodemographic and cognitive characteristics associated with these patterns of intended watch response.

The three common patterns in intended response for a daytime watch were to do nothing and continue on as before; to seek more information on smartphones, tablets, and the internet; and to pray for safety and seek shelter. While there were a number of significant associations, younger participants, those reporting prior experience with a tornado, and those with a correct knowledge of a tornado watch were less likely to seek shelter and pray for safety for a tornado watch, while increased age and weak beliefs of self-efficacy made them less likely to use technology to seek further information.

The two common patterns in intended response for a nighttime watch were to do nothing and continue on as before, or to react actively by contacting friends and family, seeking shelter, using apps to find more information, and other actions. Participants living in East Tennessee and those who believed that bodies of water offer protection from tornadoes were more likely to react actively, while those who lived in single- or multi-family homes were less likely to do so only when not taking participant income into account. When including income, wealthier participants were less likely to react actively to a nighttime tornado watch.

These results show that while sociodemographic characteristics such as age and income do play a predictive role in determining intended watch response, psychological beliefs, knowledge of tornado alerts, and past experience with tornadoes do as well. While previous studies have found that most members of the public can correctly differentiate between watches and warnings, further public education efforts on the different types of tornado alerts may aid in preventing future confusion and inappropriate reactions to these alerts. Additionally, emphasizing that one's actions before and during a tornado event can affect survival likelihood may prevent apathetic responses to future tornado events.

Chapter 5

Conclusions

5.1 Dissertation Theme

The theme of this dissertation is the exploration of hazardous weather in the Southeast in three ways: examining uniquely simultaneous hazards that can cause confusion amongst the public; assessing precipitation and synoptic patterns on HWDs in the Southeast; and identifying patterns in intended public response to tornado watches. I approached the first of these angles by intersecting simultaneous tornado and flash flood warnings in TC environments. The recommended protective actions for tornadoes and flash floods conflict, requiring those exposed to TORFF warnings with the dilemma of sheltering from one hazard while increasing vulnerability to the other in an already-chaotic setting of a TC. I evaluated the locations, areal coverage, and duration of these TORFF warnings, and then determined TC characteristics that were associated with TORFF warnings.

I approached the second angle by identifying HWDs at 40 locations over ten years in the Southeast and quantifying precipitation and synoptic weather types on these days. This process defined major patterns of precipitation on HWDs in the Southeast. Examining synoptic weather types on Southeast HWDs allows for connections to prior studies on synoptic weather climatology, which may shed light on the future of hazardous weather in the Southeast as the climate changes.

For the third angle on hazardous weather in this dissertation, I examined survey responses from Tennessee residents on their intended response to tornado warnings. I used a clustering procedure to identify commonalities in these intended responses for hypothetical tornado scenarios during both the day and night, since timing is a major factor in tornado fatality rates in the Southeast. Then, I analyzed how psychological and sociodemographic factors were associated with these patterns in intended watch response, and how these findings compared to past research on public response to tornadoes.

5.2 Major Conclusions and Future Directions

5.2.1 Uniquely simultaneous hazards: TC TORFF warnings

In Chapter 2, I used NWS warnings and archived TC track data to identify 619 instances of TORFF warnings. These dangerous hazard events occurred in 19 of 32 TCs over the 11-year study period. Geographically, TORFF warnings were most common in the Gulf and Atlantic coastal regions where TC landfalls are relatively frequent. The highest concentrations of TORFF warnings were in the states of Texas, Louisiana, and Mississippi, along the tracks of hurricanes Harvey (2017), Gustav (2008), and Isaac (2012), as well as Tropical Storm Lee (2011). These four storms, along with Hurricane Florence (2018), produced 478 of the 619, or 77.2 percent, of the total TORFF warnings in this study. This shows that the distribution of TORFF warnings per TC is skewed heavily right, with most TCs producing only a few TCs or none at all, and a select few TCs producing many.

The average TORFF warning was 508.9 km^2 in area and 27.0 minutes in length, about half the size and 70 percent as long as the average tornado warning. Over 70 percent of TORFF warnings occurred within 100 km of the coastline, and over 90 percent within 200 km of the coastline, which is notable since many densely populated areas in the Southeast are located near the coast. I used a logistic regression to determine TC characteristics that were associated with TORFF warning production. The results indicated that more intense TCs were more likely to produce at least one TORFF warning, and slower-moving TCs were more likely to produce many TORFF warnings. The six TCs that produced the most TORFF warnings each had mean post-landfall translational velocities of less than nine knots.

Since TCs frequently hit countries in the Caribbean, South and East Asia, and other global locations, future studies may examine TC TORFF occurrence outside the U.S. using either observations of tornadoes and flash floods or weather alerts analogous to NWS warnings. Future research may also include efforts to verify TORFF warnings. While TCs are capable producing widespread destruction that complicates post-event damage analysis, such a study would be useful to determine the relative level of risk posed by tornadoes and flash floods in these instances. Finally, analysis of public response to TORFF warnings would show the level of confusion amongst those who are issued TORFF warnings and perhaps determine which protective action they are most likely to take under various circumstances.

5.2.2 Precipitation and Synoptic Weather Types on HWDs

In Chapter 3, I defined hydrometeorological HWDs in the Southeast using NWS warnings for severe convective weather, floods, TCs, and winter weather. I then quantified precipitation on HWDs and used the Spatial Synoptic Classification system to define synoptic weather types on these days. Geographically, I found two precipitation maxima on HWDs: one in the lower Mississippi Valley and the other in the Carolinas. The greatest proportion of precipitation on HWDs was on Transition synoptic weather types, which indicate changing airmasses and passing frontal boundaries. However, subregional patterns indicated that locations in the lower Mississippi Valley received relatively high proportions of HWD precipitation on Moist Moderate synoptic days and seasonally during the spring, while locations in the Carolinas received high precipitation proportions on Moist Tropical days and during the summer.

These are important takeaways for future work on hazardous weather climatology in the Southeast, indicating that individual subregions may exhibit distinct hazard profile trends as Earth's climate changes. Additionally, the SSC system has been used by many other studies to examine multidecadal weather trends. Connecting hazardous mesoscale events to synoptic weather types helps serve as a spatiotemporal scaling bridge in determining the future of hazardous weather in the Southeast.

5.2.3 Intended public response to tornado watches

In Chapter 4, I used data from a survey of Tennessee residents regarding their intended responses to tornado watches. I established three common patterns in intended response to a tornado watch during the afternoon, and two common intended responses patterns for a tornado watch at night. The three common intended responses for a daytime scenario were characterized by 1) seeking more information on smartphones, tablets, and the internet; 2) praying for safety and seeking shelter; or 3) doing nothing and continuing on as before. The two common intended responses for a nighttime scenario were to respond actively, undertaking most or all of the responses listed in the survey, including contacting friends or family, using technology to seek more information, and seeking shelter; or to respond passively and continue on as before.

I then used logistic regression to determine which sociodemographic and psychological factors describing survey participants were associated with their intended response to these scenarios. I found significant associations between intended response pattern and factors such as age, income, past experience with tornadoes, knowledge of tornado alerts, and beliefs of self-efficacy in a tornado event. Participants who were older were more likely to intend to pray for safety and seek shelter and less likely to use technology during a daytime event. Those who correctly understood the definition of a tornado watch or had experienced a tornado hitting their home or building were less likely to seek shelter and pray for safety. The effects of past experience with severe weather, or lack thereof, on one's response to hazard alerts is an important avenue for future work as U.S. demographics shift and tornado-prone regions of the country become more heavily populated. Individuals who indicated that they would consult technology for more information on a tornado watch were likely to have relatively strong beliefs of self-efficacy in a tornado event and were less (more) likely to live in a single- or multi-family home (apartment or mobile home). This indicates that cognitive factors play a notable role in determining intended hazard response, as may one's confidence in sheltering options should a tornado strike.

For the nighttime scenario, those who live in East Tennessee or who believe that water bodies protect surrounding areas from tornadoes are more likely to undertake an active intended response to a tornado watch. These factors may indicate a lack of familiarity with tornadoes since water bodies in fact provide little protection, and East Tennessee is the least active region for tornadoes in the state. As in the daytime scenario, participants in single- or multi-family houses were unlikely to intend to respond actively to a tornado watch, possibly since they were confident in having adequate shelter. However, when I added income to the regression, this housing variable no longer exhibited a significant coefficient. Income, on the other hand, was negatively associated with an active intended response, indicating that wealthier participants were more likely to do nothing and continue on as before upon learning of a tornado watch.

5.3 Summary of Dissertation Contribution

In this dissertation, I have examined hazardous weather in the Southeast from the angle of unique meteorological hazards, climatological patterns that can be applied to long-term studies, and public response to hazard alerts. To determine substantive findings on these angles, I drew from a variety of data sources and techniques, including radar data, in-situ observations, derived synoptic weather types, and survey responses from human subjects. Each of the three research chapters herein are novel contributions to the field of hazards climatology that will be published in well-respected, peer-reviewed journals for dissemination to researchers and other stakeholders. I hope to continue pursuing these and other pertinent topics in the future.

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Appendix

Table A1. Number of days that an NWS warning was issued for each hazard.

City (Station)	Days with Severe Thunderstorm warnings	Days with Tornado warnings	Days with Flash Flood warnings	Days with Winter Storm, Ice Storm, or Blizzard warnings	Days with Hurricane or Tropical Storm warnings	Total HWDs
Birmingham, AL (KBMX)	71	8	46	19	2	129
Huntsville, AL (KHSV)	73	11	43	18	2	129
Montgomery, AL (KMGM)	39	5	21	6	4	71
Mobile, AL (KMOB)	77	4	53	3	31	142
Gainesville, FL (KGNV)	53	0	2	0	13	67
Jacksonville, FL (KJAX)	75	4	6	0	18	98
Miami, FL (KMIA)	36	2	5	0	18	61

Table A1 continued.

City (Station)	Days with Severe Thunderstorm warnings	Days with Tornado warnings	Days with Flash Flood warnings	Days with Winter Storm, Ice Storm, or Blizzard warnings	Days with Hurricane or Tropical Storm warnings	Total HWDs
Orlando, FL (KMCO)	65	9	0	0	8	77
W. Palm Beach, FL (KPBI)	44	7	7	0	15	68
Fort Myers, FL (KRSW)	24	3	0	0	9	33
Tallahassee, FL (KTLH)	78	3	14	3	12	102
Tampa, FL (KTPA)	44	8	2	0	19	67
Augusta, GA (KAGS)	79	3	10	12	2	101
Atlanta, GA (KATL)	52	2	18	14	2	87
Macon, GA (KMCN)	48	3	5	8	5	66
Savannah, GA (KSAV)	106	7	12	5	17	139
Evansville, IN (KEVV)	43	5	34	34	0	109
Jackson, KY (KJKL)	77	3	15	32	0	122
Lexington, KY (KLEX)	61	3	24	38	0	119
Louisville, KY (KSDF)	81	4	37	29	0	138

Table A1 continued.

City (Station)	Days with Severe Thunderstorm warnings	Days with Tornado warnings	Days with Flash Flood warnings	Days with Winter Storm, Ice Storm, or Blizzard warnings	Days with Hurricane or Tropical Storm warnings	Total HWDs
Baton Rouge, LA (KBTR)	57	8	20	8	10	96
New Orleans, LA (KMSY)	44	8	8	2	22	91
Jackson, MS (KJAN)	96	11	78	9	2	176
Tupelo, MS (KTUP)	90	5	57	14	0	139
Cape Girardeau, MO (KCGI)	47	11	34	32	0	109
Asheville, NC (KAVL)	70	3	8	56	1	138
Charlotte, NC (KCLT)	105	7	41	30	1	172
Greenville, NC (KEWN)	53	7	7	22	34	116
Greensboro, NC (KGSO)	100	4	62	36	1	181
Wilmington, NC (KILM)	24	4	15	11	33	79
Raleigh, NC (KRDU)	124	4	51	31	5	191

Table A1 continued.

City (Station)	Days with Severe Thunderstorm warnings	Days with Tornado warnings	Days with Flash Flood warnings	Days with Winter Storm, Ice Storm, or Blizzard warnings	Days with Hurricane or Tropical Storm warnings	Total HWDs
Columbia, SC (KCAE)	100	2	11	11	4	123
Charleston, SC (KCHS)	109	4	38	7	23	168
Nashville, TN (KBNA)	99	12	27	16	0	140
Chattanooga, TN (KCHA)	89	9	13	13	0	116
Memphis, TN (KMEM)	79	11	88	24	0	164
Knoxville, TN (KTYS)	106	11	6	13	0	126
Norfolk, VA (KORF)	57	8	11	20	16	104
Richmond, VA (KRIC)	49	4	11	33	3	95
Roanoke, VA (KROA)	75	1	35	48	0	150

Table A2. Number of days each non-dry SSC type and percentage that were HWDs.

City (Station)	Dry days (percent which were HWDs)	MP days (percent which were HWDs)	MM days (percent which were HWDs)	MT days (percent which were HWDs)	TR days (percent which were HWDs)
Birmingham, AL (KBMX)	1576 (0.51%)	121 (8.26%)	399 (7.02%)	1269 (4.18%)	258 (11.63%)
Huntsville, AL (KHSV)	1643 (0.55%)	148 (7.43%)	398 (7.29%)	1194 (4.02%)	267 (11.99%)
Montgomery, AL (KMGM)	1573 (0.38%)	83 (3.61%)	322 (4.04%)	1381 (2.39%)	277 (5.05%)
Mobile, AL (KMOB)	1274 (0.55%)	70 (1.43%)	359 (10.31%)	1698 (3.77%)	239 (11.72%)
Gainesville, FL (KGNV)	1311 (0.23%)	33 (0.00%)	307 (3.58%)	1729 (2.08%)	232 (6.90%)
Jacksonville, FL (KJAX)	1107 (0.00%)	57 (0.00%)	457 (4.81%)	1790 (3.02%)	241 (9.13%)
Miami, FL (KMIA)	547 (0.37%)	9 (0.00%)	324 (4.01%)	2561 (1.29%)	209 (5.26%)
Orlando, FL (KMCO)	977 (0.31%)	18 (0.00%)	356 (3.93%)	2034 (2.11%)	228 (7.46%)
W. Palm Beach, FL (KPBI)	623 (0.00%)	9 (0.00%)	300 (5.67%)	2449 (1.31%)	267 (5.62%)
Fort Myers, FL (KRSW)	1031 (0.39%)	14 (0.00%)	229 (2.62%)	2149 (0.74%)	196 (3.57%)
Tallahassee, FL (KTLH)	1401 (0.14%)	34 (2.94%)	262 (5.34%)	1669 (3.59%)	261 (7.28%)
Tampa, FL (KTPA)	979 (0.00%)	18 (0.00%)	298 (6.38%)	2117 (1.75%)	238 (4.62%)

Table A2 continued.

City (Station)	Dry days (percent which were HWDs)	MP days (percent which were HWDs)	MM days (percent which were HWDs)	MT days (percent which were HWDs)	TR days (percent which were HWDs)
Augusta, GA (KAGS)	1701 (0.53%)	86 (10.47%)	350 (3.14%)	1227 (3.59%)	259 (10.04%)
Atlanta, GA (KATL)	1401 (0.43%)	139 (6.47%)	477 (3.98%)	1259 (3.02%)	274 (5.47%)
Macon, GA (KMCN)	1642 (0.37%)	109 (6.42%)	387 (2.07%)	1239 (2.58%)	248 (4.84%)
Savannah, GA (KSAV)	1335 (0.60%)	71 (5.63%)	355 (5.35%)	1598 (5.19%)	279 (8.96%)
Evansville, IN (KEVV)	1814 (0.72%)	266 (7.89%)	353 (4.53%)	864 (4.17%)	319 (6.58%)
Lexington, KY (KLEX)	1710 (0.58%)	337 (5.64%)	359 (4.46%)	856 (4.56%)	370 (9.19%)
Louisville, KY (KSDF)	1654 (0.54%)	288 (6.60%)	376 (4.26%)	961 (5.31%)	371 (11.59%)
Baton Rouge, LA (KBTR)	1222 (0.33%)	76 (7.89%)	333 (4.20%)	1696 (2.42%)	295 (9.83%)
New Orleans, LA (KMSY)	1052 (0.19%)	64 (0.00%)	319 (6.89%)	1916 (2.04%)	301 (9.30%)
Jackson, MS (KJAN)	1498 (0.40%)	99 (7.07%)	391 (9.46%)	1368 (6.21%)	291 (14.09%)
Tupelo, MS (KTUP)	1679 (0.48%)	142 (4.93%)	357 (7.84%)	1140 (4.91%)	300 (12.33%)

Table A2 continued.

City (Station)	Dry days (percent which were HWDs)	MP days (percent which were HWDs)	MM days (percent which were HWDs)	MT days (percent which were HWDs)	TR days (percent which were HWDs)
Asheville, NC (KAVL)	1790 (1.45%)	209 (17.22%)	502 (4.78%)	865 (4.62%)	268 (4.48%)
Charlotte, NC (KCLT)	1614 (0.43%)	164 (12.80%)	445 (9.21%)	1129 (6.64%)	298 (9.40%)
Greenville, NC (KEWN)	1303 (0.46%)	103 (11.65%)	427 (3.04%)	1382 (3.76%)	370 (7.57%)
Greensboro, NC (KGSO)	1669 (0.66%)	194 (14.43%)	466 (7.51%)	1005 (7.56%)	316 (9.81%)
Wilmington, NC (KILM)	1273 (0.39%)	121 (5.79%)	445 (3.60%)	1494 (1.81%)	306 (7.19%)
Raleigh, NC (KRDU)	1592 (0.82%)	182 (11.54%)	439 (7.06%)	1145 (8.21%)	291 (10.65%)
Columbia, SC (KCAE)	1633 (0.80%)	91 (7.69%)	348 (3.45%)	1287 (5.28%)	279 (7.89%)
Charleston, SC (KCHS)	1318 (0.91%)	97 (8.25%)	339 (6.78%)	1627 (6.45%)	270 (7.41%)
Nashville, TN (KBNA)	1542 (0.32%)	243 (4.12%)	432 (7.18%)	1005 (5.27%)	412 (9.71%)
Chattanooga, TN (KCHA)	1676 (0.24%)	143 (6.29%)	424 (5.90%)	1090 (4.68%)	314 (8.60%)
Memphis, TN (KMEM)	1522 (0.39%)	190 (8.42%)	402 (6.71%)	1225 (6.20%)	298 (12.08%)
Knoxville, TN (KTYS)	1605 (0.50%)	222 (4.95%)	515 (4.27%)	971 (5.87%)	336 (8.33%)

Table A2 continued.

City (Station)	Dry days (percent which were HWDs)	MP days (percent which were HWDs)	MM days (percent which were HWDs)	MT days (percent which were HWDs)	TR days (percent which were HWDs)
Norfolk/Virginia Beach, VA (KORF)	1505 (0.80%)	176 (5.68%)	524 (2.86%)	1127 (3.99%)	309 (6.80%)
Richmond, VA (KRIC)	1654 (0.79%)	189 (10.05%)	494 (1.82%)	986 (3.35%)	327 (6.42%)
Roanoke, VA (KROA)	1796 (0.89%)	239 (12.55%)	491 (6.11%)	831 (6.74%)	291 (6.19%)

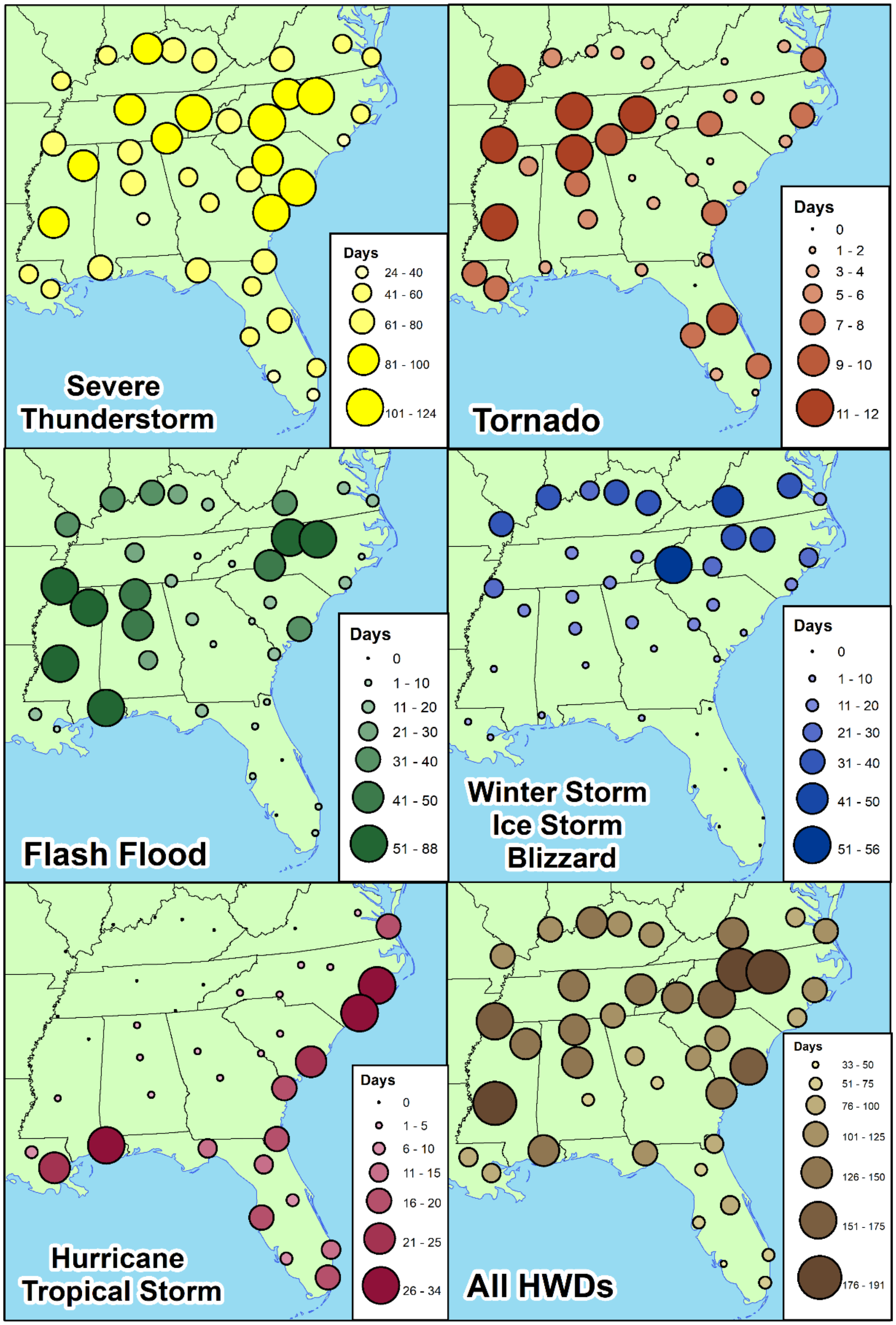

Figure A1. Number of days on which an NWS warning was issued for each hazard.

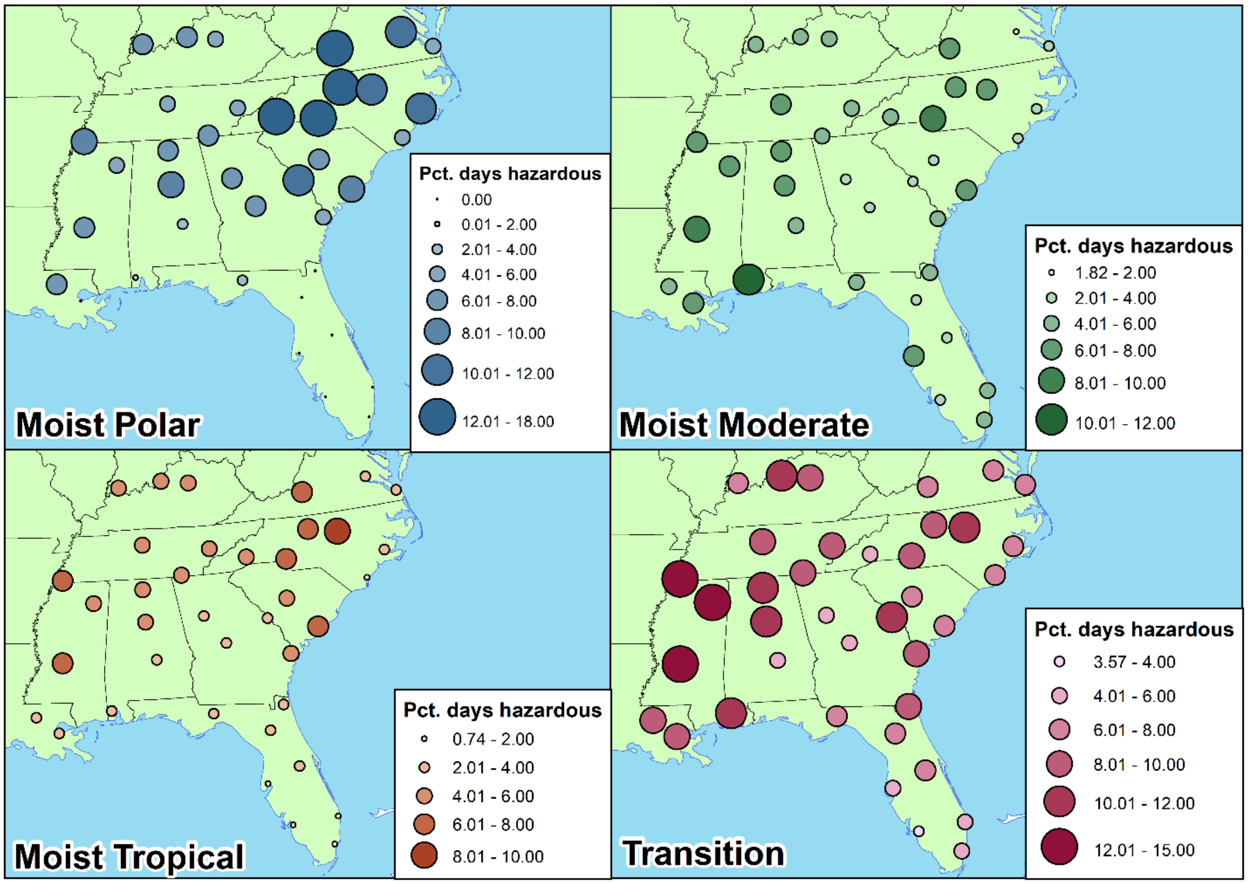

Figure A2. Proportion of HWDs for each non-dry SSC type.

Vita

Daniel Burow grew up in suburban Minneapolis, Minnesota before earning a bachelor's degree in Meteorology with minors in Math and Geography from Valparaiso University (Valparaiso, IN) in 2015. He then earned his master's degree in Geography from the University of North Dakota (Grand Forks, ND) in 2017 and enrolled in the PhD program in Geography at the University of Tennessee, Knoxville the following fall semester. After graduating from UTK, the next step in his career will be an Assistant Professor of Meteorology position at Embry-Riddle Aeronautical University (Daytona Beach, FL).